“Hi, I’m a smoking cessation chatbot!”

The effects of empathy and personalisation on satisfaction with the conversation, attitude towards using the chatbot and intention to quit smoking

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Abstract

The focus of this study was on an e-health chatbot that could provide its users with information and advice regarding smoking cessation. The aim of this study was to assess the possible effects of the use of personalisation and empathy by this chatbot on satisfaction with the conversation, attitude towards using the chatbot and intention to quit smoking. To achieve this aim, a 2 (personalisation/no personalisation) x 3 (no empathy/cognitive empathy/affective empathy) experimental design was created. Six chatbots were created using the online program Flow.ai, one for each of the experimental conditions. A general conversational script was written for the chatbots and adapted to fit each specific condition. The conversation followed the 5A's model for brief smoking interventions and provided information and advice to the users. Furthermore, a survey was created using the Qualtrics software. In the end, a total of 156 participants were recruited.

Results of the study showed no statistically significant differences between the empathy conditions, nor did they show significant main effects of personalisation or empathy on satisfaction with the conversation, attitude towards using the chatbot and intention to quit smoking. There were also no significant interaction effects of personalisation and empathy on the dependent variables. Although the study produced no significant findings there were some interesting trends to be observed from the results. These included participants in the affective empathy conditions reporting the highest scores on satisfaction and intention to quit smoking, followed by those in the cognitive empathy conditions. Participants in the no empathy conditions reported the lowest scores. There were virtually no differences in reported scores for attitudes. Furthermore, affective empathy and cognitive empathy seemed to interact with personalisation in contradicting ways. The main implications of the current study are to keep in mind the fact that empathy should not be seen as a single construct and to preferably implement affective empathy in e-health interventions. Furthermore, working with physicians when developing e-health chatbots is encouraged. Even though this study did not produce any significant results and the manipulations were weak, it should be noted that participants still reported high scores on all variables. This raised the important question about whether or not chatbots are, by default, perceived as personal and/or empathic which is a valuable insight that should be taken into account by chatbot developers and researchers for future work.

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1. Introduction

Smoking is a worldwide health problem and results in 8 million deaths worldwide each year (Wang, Zhang, Ip & Lau, 2018; WHO, https://www.who.int/health-topics/tobacco#tab=tab_1). Therefore, smokers who are aware of the risks often want to quit to avoid these negative outcomes (WHO, https://www.who.int/activities/quitting-tobacco). Whilst it remains difficult to change health behaviours, mobile health interventions have shown to be successful (Fitzpatrick, Darcy, & Vierhile, 2017; Perski, Blandford, Ubhi, West, & Michie, 2017; Wang et al., 2018). These new forms of healthcare interventions belong to the emerging field of e-health, which uses interactive technologies to discuss disease prevention and management (Eng, as cited in Strecher, 2007).

One type of technology that is increasingly being implemented as e-health interventions is chatbots. A chatbot can be defined as a computer program that uses natural language to interact with users and simulate a human-like conversation (Shawar & Atwell, 2007). Chatbots can benefit healthcare systems by providing relevant health information, services, recommendations, and even interventions to patients in a cost-effective and time conserving way (Fitzpatrick et al., 2017; Palanica, Flaschner, Thommandram, Li, & Fossat, 2019; Pereira & Diaz, 2019; Perski, Crane, Beard, & Brown, 2019).

An important advantage of chatbots is that they can serve as relational agents by employing communication techniques that help establish a relationship between the chatbot and its user. This is especially important in healthcare-oriented chatbots, as research has shown that relational behaviours can improve patient satisfaction as well as health outcomes (Bickmore, Gruber & Picard, 2005). More specifically, a good relationship between a counsellor and a participant for brief smoking cessation interventions can increase the probability that the participant will make a quitting attempt (Klemperer, Hughes, Callas & Solomon, 2017). One important relational behaviour that has produced promising results regarding chatbots for smoking cessation is empathy.

Empathy can be defined as the process of trying to understand and respond to someone else's feelings or expressions of their emotions without actually experiencing them (Hogan, 1969). It is important to implement empathy into e-health systems as it is associated with improved patient satisfaction and health outcomes (Bickmore et al., 2005). Furthermore, studies show that empathy has a positive effect on quitting attempts for alcoholism and smoking (Ellis et al., 2017; Shen, 2011).

Research on expressions of empathy by e-health chatbots has shown that it also improves people's attitudes towards those chatbots (Bickmore et al., 2005; Liu & Sundar, 2018).

However, Liu and Sundar's (2018) study produced contradicting results and showed that some participants found expressions of empathy by an e-health chatbot slightly unsettling because it created a feeling of eeriness (Liu & Sundar, 2018). Additionally, Klemperer et al. (2017) found that empathy use by a counsellor led to a decrease in the probability of a patient making a quitting attempt. The contradicting results of these studies show that the effectiveness of empathy in health advice related chatbots remains inconclusive. Therefore, this study aims to fill that gap by investigating the effects of the use of empathy by a smoking cessation chatbot on satisfaction with the conversation, attitude towards the chatbot and intention to quit smoking.

Next to empathy, another relational behaviour that has produced promising results regarding smoking cessation and the use of chatbots is personalisation. Personalisation in e-health interventions refers to responding to user input in order to create personalised content (Kaner et al., 2017). Examples of personalisation are calling users by their name and asking for and referring back to personal information (Dijkstra & Ballast, 2012; Van Hooijdonk & Liebrecht, 2018). Personalisation is a useful tool for getting a person to do or change something because they feel directly addressed. A study by Dijkstra and Ballast (2012) showed that mentioning a patient's name in persuasive messages resulted in a higher number of quitting attempts. Personalisation has also been proven to increase user satisfaction (Pereira & Diaz, 2019).

Whilst there are various studies that indicate the positive effects of personalisation in healthcare interventions, others specify a clear desire for anonymity (Fogg, 2002; Pereira & Diaz, 2019). This is specifically the case when discussing sensitive healthcare issues such as addictions. When talking about sensitive issues, people prefer an online intervention because it adds to the feeling of anonymity and takes away from feelings of intimidation and judgement (Brandtzaeg & Folstad, 2017; Frisby, Bessell, Borland, & Anderson, 2002; Nadarzynski, Miles, Cowie, & Ridge, 2019). Since previous studies share contradicting recommendations about whether or not e-health interventions should be personalised, the second, and final, goal of this study is to investigate what effects personalisation in a smoking cessation chatbot might have on satisfaction with the conversation, attitude towards the chatbot and the intention to quit smoking. To investigate the aforementioned goals and assess the effects of personalisation and empathy in a smoking cessation chatbot, the following research question has been formulated:

RQ: “To what extent do personalisation and empathy in a smoking cessation chatbot have an effect on satisfaction with the conversation, attitude towards the chatbot and intention to quit smoking?”

2. Theoretical Framework

2.1 Smoking: dangers and interventions

Smoking is one of the leading risk factors for health problems such as respiratory diseases, cancers and cardiovascular diseases worldwide. These health problems have a seriously negative effect on the smoker’s quality of life (Grolleman, Van Dijk, Nijholt, & Van Ernst, 2006; Wang et al., 2018). According to data from the World Health Organization (WHO) tobacco kills around fifty per cent of the people who use it, which leads to 8 million people dying of the results of tobacco use each year (World Health Organisation, https://www.who.int/healthtopics/tobacco#tab=tab_1).

Smoking is a devastating issue and the most important thing a smoker can do to improve their health is to quit (Frisby et al., 2002). However, trying to quit smoking often poses a huge challenge. The main reason for this is its highly addictive nature (Grolleman et al., 2006). Therefore, smoking cessation interventions are important measures in helping people to quit (Kotz, Batra & Kastaun, 2020).

There are numerous strategies, methods, and intervention techniques used for smoking cessation. This list includes more classical techniques such as reading books on smoking cessation, getting advice from a physician or a pharmacist, medication and behavioural counselling (Kotz et al., 2020). The invention of the internet, however, has given rise to a new form of healthcare that offers new, digital possibilities: e-health. E-health can be defined as “an emerging field in the intersection of medical informatics, public health, and business, referring to health services and information delivered or enhanced through the Internet and related technologies” (Eysenbach, 2001, p.1).

These new, digital interventions include delivering smoking cessation information via the internet, creating online support groups and providing online personalised self-help materials and behavioural treatments (Frisby et al., 2002). Studies on such digital interventions regarding behavioural change have found promising results on several outcome factors. First of all, Brendryen, Drozd and Kraft (2008) showed that automated support through a digital intervention can have positive effects on long-term behaviour change.

Iacovello et al. (2017) found that the most frequently used function of an app for smoking cessation was the function that allowed people to receive personalised messages. They also found a possible association between frequent usage of the app and intention to quit smoking (Iacovello et al., 2017).

Online interventions such as the ones mentioned above and other digital interventions, opportunities and smartphone apps are all part of the emerging field of e-health (Brendryen & Kraft, 2007; Brendryen et al., 2008; Chevalking, Allouch, Brusse-Keizer, Postel & Pieterse, 2018; Iacoviello et al., 2017). Another way to offer people digital interventions is through the use of chatbots. Over the last couple of years, there has been a growing interest in chatbots as e-health applications, which raises the question if this technology can be as useful for digital interventions as these other technologies have been (Bates, 2019; Dubosson, Schaer, Savioz & Schumacher, 2017).

2.2. Chatbot Opportunities

2.2.1 Chatbots in E-Health

A chatbot can be defined as a computer program that uses natural language to interact with users and simulate a human-like conversation (Kocaballi et al., 2019; Shawar & Atwell, 2007). Chatbots are being increasingly implemented as e-health interventions to assist people in several ways. They can provide health information and services, collect data, recommend treatments, and can even be used for therapy purposes (Denecke, Tschanz, Dorner, & May, 2019; Fitzpatrick et al., 2017; Palanica et al., 2019). The main goal for the development of e-health chatbots is to provide an alternative way of helping people whilst simultaneously reducing costs in terms of finances and time (Pereira & Diaz, 2019).

There are three aspects of e-health as discussed by Eysenbach (2001) and Wicks, Stamford, Grootenhuis, Haverman and Ahmed (2013) that are relevant to the use and possible success of chatbots as e-health interventions. The first of these aspects is increased efficiency. In contrast to their human counterparts, chatbots can be operative twenty-four hours a day, making them easier to reach and thus more efficient (Palanica et al., 2019). As an online tool, chatbots also have the ability to remotely deliver advice or counselling to larger audiences in a cost-effective way, which improves healthcare accessibility (Bates, 2019; Pereira & Diaz, 2019; Wicks et al., 2013).

The second aspect of e-health that is relevant to the use of chatbots is enhancing quality of care. This includes being able to maintain contact with patients and gaining feedback reports from them regarding healthcare and satisfaction (Wicks et al., 2013).

In general, chatbots allow for quick and easy user engagement through text-based messaging that is available at all hours of the day (Pereira & Diaz, 2019). This text-based messaging involves the chatbot following a pre-determined conversation tree to guide the user through the conversation. By doing this, the chatbot conversations can be used to easily collect data and feedback from a user (Denecke et al., 2019). Furthermore, chatbots can be used to monitor people's health, connect patients to the right healthcare workers, and book appointments, which makes them a convenient and accessible tool for maintaining contact with patients (Bates, 2019).

The third aspect of e-health that is relevant to the use of chatbots is empowerment. More specific: empowering individuals to take care of their own health and preferably change their unhealthy behaviours. This can be achieved by sharing medical information, sharing information about treatments and providing self-management interventions (Wicks et al., 2013), all of which chatbots are capable of doing (Bates, 2019; Hauser-Ulrich, Künzli, Meier-Peterhansen & Kowatsch, 2020). Important here is that making people understand the implications of specific health conditions, as well as motivating and encouraging them, will empower them to take action in managing their own health (Denecke et al., 2019; Peirera & Diaz, 2019). Even though chatbot technology is still going through various stages of development and improvement, it has been shown to be versatile and is therefore likely to take on an expanding role within the field of e-health (Bates, 2019).

2.2.2 Chatbots for Smoking Cessation

Little research has been done on the use of chatbots for smoking cessation interventions, but the few studies that have been conducted show promising results. Wang et al. (2018) conducted an experiment for which they implemented a chatbot in social media Instant Messaging (IM). Participants (N = 205) could talk to each other and the chatbot, which would respond to them or notify them of information regarding smoking cessation. Participants were found to engage quicker with conversations when the chatbot was involved and had a higher success rate in refraining from smoking when they were part of more conversations (Wang et al., 2018).

Perski et al. (2019) added a motivational chatbot to an already existing smoking cessation application. This chatbot checked in with users twice a day but was also available at any given moment when users felt like they needed support.

Their results show that participants in the chatbot conditions were more engaged with the application than others in the control condition (Perski et al., 2019). The results also indicate that participants in the chatbot conditions had greater chances of quitting success. However, the authors note that these results should be interpreted with caution since it was unclear whether this was because of the chatbot or possible interaction between the chatbot and other parts of the app. Nevertheless, the possibility of increased quitting success when using a chatbot is promising for future research.

Finally, Calvaresi et al. (2019) also implemented a chatbot into social media messaging for supporting a smoking cessation program. This chatbot could help users track their cigarette consumption to create a clear smoker profile. Receiving this profile made smokers more motivated to try and quit. Eventually, 28.9% of all participants (N = 270) succeeded in their quitting attempt. This was 10% more than usual, which indicates that using chatbot technologies for smoking cessation has promising potential.

2.3 Relational agents

Research on counsellor-patient relationships for smoking cessation interventions has shown that a good relationship and working alliance between a counsellor and their patient can increase the probability of a quitting attempt (Klemperer et al., 2017). Research has also highlighted the importance of a good relationship between a healthcare provider and their patient and has shown this can also be established between a relational agent and a patient (Bickmore et al., 2005).

Relational agents are computer agents that are designed to form a social-emotional relationship with their users over a longer period of time (Bickmore et al., 2005). This relationship is built by establishing trust and a working alliance with the user which is the result of implementing relational behaviours into the agent (Bickmore et al., 2005; Bickmore & Picard, 2005; Bickmore & Schulman, 2006; Bickmore et al., 2010). These relational behaviours can be both verbal as well as non-verbal and include social dialogue, humour, reciprocal self-disclosure, personalisation and empathy (Bickmore et al., 2005; Bickmore et al., 2010).

Research on the use of relational agents in the field of healthcare has produced positive results. Prochaska et al. (2012) conducted a longitudinal study in which people with substance use concerns spend eight weeks talking to a relational agent that was used for delivering brief text-based conversations (N = 1548). They found that using this relational agent resulted in a significant decrease in substance abuse and cravings for participants in the corresponding condition (Prochaska et al., 2012).

Kabir, Schulman and Abdullah (2019) investigated the use of relational agents to promote health behaviour change in high-, medium- and low-income countries. They found that whilst these agents cannot replace actual healthcare workers, they are a source of additional support and could play a significant role in providing healthcare interventions (Kabir et al., 2019). Furthermore, Bickmore et al. (2010) found that relational agents can be seen as more approachable than actual healthcare workers and that participants were prepared to continue working with the agent. Relational behaviours used by a chatbot can also create more positive attitudes towards the agent, more treatment participation and improved health behaviours (Bickmore et al., 2005).

For this current study, the focus will be on two relational behaviours: empathy and personalisation. Empathy in particular is of specific interest as it has been called a critical feature in the establishment of trust and working alliance (Bickmore & Schulman, 2006). Personalisation is important because it has been found to improve several factors in human-agent interaction such as cooperation and engagement (Liao, Davis, Geyer, Muller & Shami, 2016).

2.3.1 Empathy

Empathy is a critical feature in establishing trust and working alliances and therefore is a key factor in forming relationships (Bickmore et al., 2005; Bickmore & Schulman, 2006). Empathy is defined as the process of trying to understand and respond to someone else's emotions or expressions of those emotions (Hogan, 1969). In their literature review regarding empathy, Cuff, Brown, Taylor, and Howat (2016) come to several conclusions about the construct. One of the most important conclusions they come to is that empathy itself is not a singular construct. Instead, it consists of two components that help produce emotional understanding: cognitive empathy and affective empathy (Cuff et al., 2016; Shamay-Tsoory, Aharon-Perets & Perry, 2009).

Cognitive empathy refers to actions of trying to comprehend someone else's emotions and their perspective, to show understanding for what they might be feeling without matching their emotions (Preston & De Waal, 2002; Shamay-Tsoory et al., 2009; Vossen, Piotrowski & Valkenburg, 2015). Affective empathy refers to sharing and indirectly experiencing the emotions someone else is feeling and is sometimes also referred to as emotional empathy (Mehrabian & Epstein, 1972; Reniers, Corcoran, Drake, Shryane & Völlm, 2010; Shamay-Tsoory et al., 2009).

Empathy in E-health and Chatbots. Research regarding the use of empathy in chatbots shows that even though chatbots might not be able to understand and convey emotion at the same level as humans do, they can still be perceived as empathic by their users. Fitzpatrick et al. (2017) investigated the use of an automated conversational agent called Woebot as a way to deliver behaviour therapy on mental health. A specifically interesting result from their study was that several of their participants expressed that what they liked most about talking to the chatbot was that it came across as being empathic (Fitzpatrick et al., 2017). Several other studies regarding human-computer interaction and chatbot conversations show that empathy can have a positive effect on patient satisfaction, treatment outcomes, effectiveness and attitude towards a chatbot (Bickmore et al., 2005; Clark, 2010; Klein, Moon & Picard, 2002; Pereira & Diaz, 2019).

Empathy is also said to be a necessity in therapeutical interactions (Pereira & Diaz, 2019). A study regarding empathy in a computer-delivered intervention to help people stop drinking showed that empathic messages made people feel more supported and increased their intention to stop (Ellis et al., 2017). Research regarding smoking cessation public service announcements also showed that empathy had a persuasive effect on motivating people to stop smoking (Shen, 2011).

However, these studies did not make a distinction between cognitive and affective empathy. Instead, they discuss it as a single construct. This can influence the validity of their results because cognitive and affective empathy might be perceived differently. An example of looking at empathy as a single construct can be seen in the study of Klein et al. (2002) who used computer messages to respond to user frustration. One of their conditions involved computer messages that acknowledged the user's emotions but did not indicate any sharing of those emotions, which suggests that the type of empathy used in their study was closer to cognitive empathy than affective empathy. There is no mention of this though, nor does there seem to be a clear distinction between which type of empathy studies that discuss empathy as a single construct use more often.

In regards to chatbots, it is important to differentiate between these types of empathy because they might be perceived differently by users. A chatbot expressing it understands emotion (cognitive empathy) might be accepted, but a chatbot that acts like it is able to experience emotion (affective empathy) might be perceived as disturbing because it is still a computer program. Therefore, Liu and Sundar (2018) looked at both types of empathy in their study.

They conducted an experimental study in which they created several versions of a health advice chatbot that discussed personal problems (i.e. sexually transmitted diseases) to investigate the effects of cognitive and affective empathy on how the chatbot was perceived (*N* = 88). Their results show that the two types of empathy can have different effects (Liu & Sundar, 2018). Both the affective and the cognitive empathy conditions of the chatbot were more positively evaluated than the advice-only condition. However, the cognitive empathy condition was perceived as less supportive than the affective empathy condition. Liu and Sundar (2018) argue that this could be because the messages in the cognitive empathy condition might sound more detached. Furthermore, there were some contradicting results regarding how the chatbots using empathy made people feel. Some participants appreciated an empathic chatbot because it seemed to be more supportive of their issues, yet for others, it created an eerie sensation that was a little unsettling (Liu & Sundar, 2018).

Whilst chatbots are likely to gain an expanding role in the healthcare sector, there are still people who are sceptical of the technology and its abilities (Bates, 2019; Palanica et al., 2019). Palanica et al. (2019) conducted a study in which physicians were allowed to share their opinions on the implementation of chatbots as an e-health intervention. One of their findings was that 72% of the physicians who participated in their study (*N* = 100) did not believe that chatbots can understand or display human emotions (Palanica et al., 2019).

Various researchers have mentioned that a chatbot should always show a minimal level of empathy and that empathy is a prominent factor in positive treatment and therapy outcomes (Clark, 2010; Pereira & Diaz, 2019; Zumstein & Hundertmark, 2017). Previous research has also shown that the use of empathy in chatbots and smoking cessation interventions can have positive effects on user satisfaction, attitude towards the chatbot and people's intention to change unhealthy behaviour (Ellis et al., 2007; Liu & Sundar, 2018; Fitzpatrick et al., 2017; Pereira & Diaz, 2019; Shen, 2011). Because empathy, in general, has been proven to lead to better results on the outcome factors investigated in this study, it can be expected that the use of both forms of empathy in a smoking cessation chatbot will lead to more positive results than when there is no use of empathy. Based on these expectations, H1 and H2 have been formulated.

H1: Affective empathy will result in higher satisfaction with the conversation (H1a), a more positive attitude towards the chatbot (H1b) and a higher intention to quit smoking (H1c) than no empathy.

H2: Cognitive empathy will result in higher satisfaction with the conversation (H2a), a more positive attitude towards the chatbot (H2b) and a higher intention to quit smoking (H2c) than no empathy.

Whilst Liu and Sundar (2018) found that cognitive and affective empathy both resulted in better chatbot evaluations than the condition with no empathy, they also found a difference between these two types of empathy. Their results showed that participants who had been part of the affective empathy condition felt more supported by the chatbot than those in the cognitive empathy condition (Liu & Sundar, 2018). Support is an important factor within digital interventions and has been proven to have positive effects, including a significant effect on long-term behaviour change and an increased willingness to quit (Brendryen et al., 2008; Ellis et al., 2017). Since both types of empathy are expected to have positive effects on the outcome variables, but affective empathy has previously led to an increased feeling of support, it can be expected that affective empathy will lead to better results than cognitive empathy. Therefore, H3 has been formulated.

H3: Affective empathy will result in higher satisfaction with the conversation (H3a), a more positive attitude towards the chatbot (H3b) and a higher intention to quit smoking (H3c) than cognitive empathy.

2.3.2 Personalisation

Personalisation in e-health can be defined as responding and referring to user input in order to provide them with personalised content (Kaner et al., 2017). Personalisation is an important feature in relationship formation within human-agent interaction as it has been shown to improve factors such as engagement and cooperation (Liao et al., 2016). However, personalisation within the field of e-health has also shown some contradicting results. According to Fan and Poole (2006), technological innovations have provided new opportunities for personalisation to become more effective and applicable. Personalisation as a construct has been studied in various scientific disciplines throughout the years, yet the diversity of these disciplines as well as the many ways in which personalisation can be operationalised has created a lack of consensus on how to best define it (Fan & Poole, 2006).

P**ersonalisation in e-health and chatbots.** Personalisation in e-health interventions is mainly achieved by using user input and referring or responding to that input to produce personalised content (Kaner et al., 2017). Personalisation in chatbot technology can be achieved through message personalisation. Therefore, personalisation within this current study is defined as incorporating information in a message to specifically address an individual (Dijkstra, 2014; Dijkstra & Ballast, 2012; Van Hooijdonk & Liebrecht, 2018).

There are several ways in which this type of personalisation can be achieved. One of these is to address an individual by using their name. Dijkstra and Ballast (2012) studied the effects of addressing people by their name in persuasive messages regarding smoking cessation. Their results showed that name mentioning was successful such that there was a higher rate of quitting attempts and a higher intention to quit from participants who received the personalised messages (Dijkstra & Ballast, 2012).

Another way to implement personalisation into messages is by collecting information from an individual and using that to provide personalised responses, feedback, information or recommendations (Fadhil, 2018; Fadhil & Gabrielli, 2017; Hsu, Zhao, Liao, Liu, & Wang, 2017; Kocaballi et al., 2019). By asking a user questions and using the provided information to generate personalised responses and recommendations chatbots have the ability to increase effectivity as well as engagement, self-empowerment in changing health behaviours and satisfaction (Bates, 2019; Fadhil & Gabrielli, 2017; Kadariya et al., 2019; Kocaballi et al., 2019). Furthermore, personalisation in e-health interventions is said to provide similar outcomes to those that clinic interventions would have and is a key factor for succeeding in behavioural change (Calbimonte, Calvaresi, Dubosson & Schumacher, 2019; Calvaresi et al., 2019). Kadariya et al. (2019), in their study regarding a personalised chatbot for asthma self-management, found that chatbots were more effective when they were able to retrieve information from their user and use this to generate personalised responses.

Anonymity in e-health and chatbots. Although personalisation can have positive effects on various factors, it is unclear whether personalisation is always favoured. In a mapping study regarding e-health chatbots for behaviour change, Pereira and Diaz (2019) found that patients sometimes prefer a feeling of anonymity. This is especially true for situations that concern sensitive healthcare issues, such as dealing with an addiction. In these situations, the possibility to have an anonymous interaction becomes an important reason for people to interact with a chatbot (Fogg, 2002; Pereira & Diaz, 2019).

hatbots create a feeling of anonymity and have no bias towards any type of patient demographics, such as gender or race, which causes them to be better suited to help in specific situations such as having to disclose potentially stigmatizing information (Palanica et al., 2019). This is in line with Lucas et al. (2017), who mention that people are less willing to disclose such information with another person. The results of a study by Frisby et al. (2002) showed that online smoking cessation interventions were more beneficial than face-to-face interventions because of the added feeling of anonymity. One of their participants mentioned feeling uncomfortable with talking to a health professional about addictions and quitting, and another mentioned that the online intervention meant they didn't have to talk to anyone that might make them feel bad (Frisby et al., 2002). Brandtzaeg and Folstad (2017) also mention that one of the main reasons why people sometimes prefer getting help from a chatbot is because a chatbot makes them feel less intimidated or judged.

With regard to whether or not personalisation should be used in healthcare interventions, previous research has shown mainly positive results. Talking to a chatbot about health problems, in general, creates a more secure, anonymous setting than discussing similar problems with another person does (Pereira & Diaz, 2019). This suggests that talking to an e-health chatbot should make people feel at ease. Furthermore, the review by Pereira and Diaz (2019) shows that personalisation is a main enabler for using chatbot technologies in e-health and has positive effects on various health problems and behaviours. Consequently, when adding personalisation to chatbot messages this could create a useful balance: people might still regain an overarching, increased feeling of anonymity whilst on the conversational level could be more appreciative of the chatbot because it connects with them. Based on this expectation, H4 has been formulated.

H4: Personalisation will result in higher satisfaction with the conversation (H4a), a more positive attitude towards the chatbot (H4b) and a higher intention to quit smoking (H4c) than no personalisation.

Furthermore, there is little research combining empathy and personalisation in chatbot interventions. However, both of these conversational behaviours have been proven to have mainly positive effects on the outcome factors investigated in this study. Pereira and Diaz (2019) also mention that combining empathy and personalised aspects can lead to improved patient satisfaction.

To investigate whether the combination of personalisation and empathy could lead to stronger results H5 has been formulated based on the expectation that if both behaviours lead to positive effects on their own, they might lead to even stronger positive effects when combined.

H5: There will be an interaction effect between empathy and personalisation on satisfaction with the conversation (H5a), attitude towards the chatbot (H5b) and intention to quit smoking (H5c) such that there will be stronger positive effects when empathy and personalisation are combined than for no empathy and personalisation.

3. Method

3.1 Research Design

The main aim of this study was to investigate the effects of personalisation and empathy on satisfaction with the conversation, attitude towards the chatbot and intention to quit smoking. To test the hypotheses a 3 (cognitive empathy/affective empathy/no empathy) X 2 (personalisation/no personalisation) between-subjects experimental design has been used.

3.2 Participants

Participants for this study were recruited through convenience sampling (mainly via social media channels including Facebook, Whatsapp, Instagram and LinkedIn). At the start, there were two criteria participants needed to adhere to. First of all, participants needed to be eighteen years or older to participate in the study. This criterion was set because it was expected that most participants would be Dutch and the Dutch law prohibits the sale of tobacco products to anyone under eighteen. Secondly, all participants had to be smokers of tobacco products. These criteria were both mentioned in the recruitment posts. To calculate the appropriate sample size a power analysis with the program G*Power has been performed. In order to detect a medium sized effect ($f = 0.25$) with 80% power in a two-way between-subjects ANOVA (six groups, $\alpha = .05$) the G*Power program suggested a total number of 155 participants.

Unfortunately, recruiting participants with the criterion that they had to be smokers of tobacco products proved to be challenging. To ensure that there were enough participants for the data to be analysed, the decision was eventually made to include non-smokers as well.

For this, a small section was added to the questionnaire in which participants were asked to imagine they were a smoker if they were not. This meant that most participants had to work with a hypothetical scenario in which they imagined they were smokers. The implications this had for interpreting the results will be discussed in the discussion section of this thesis.

3.3 Materials

For this study, six versions of an online chatbot for smoking cessation advice and information have been created. Since the chatbots differed based on the experimental conditions, a general script for the chatbot conversation was written to ensure that the conversational messages did not differ subsequently outside of the manipulations. Once this script was finished, it could be adapted for each of the six chatbot conditions (Table 1).

Table 1.

Experimental conditions.

Condition	**Empathy**	**Personalisation**
1.	No empathy	No personalisation
2.	No empathy	Personalisation
3.	Cognitive empathy	No personalisation
4.	Cognitive empathy	Personalisation
5.	Affective empathy	No personalisation
6.	Affective empathy	Personalisation

Next to the development of the six chatbot conditions, a survey was created using the online survey software Qualtrics. This survey included an introduction, an informed consent form, two criteria check questions, demographic questions, an explanation of the experiment and a link to one of the chatbots, experimental questions, the option to fill in any additional remarks and a debriefing. The full survey can be found in Appendix A, the informed consent form in Appendix B and the debriefing in Appendix C.

3.3.1 Chatbots

The different versions of the smoking cessation chatbot used in this study have been created via the online platform Flow.ai. This platform offered a variety of options and built-in functions, such as allowing the user free text input as well as the use of buttons or quick replies to restrict input.

According to Bickmore et al. (2005), there is still a way to go in understanding natural language input, which is why constraining a user's input could help the chatbot program create a better understanding of the user's wants, needs and intents. Therefore, whilst creating the different versions of the chatbot, the user input was mostly restricted by providing them with buttons more often than free text input. These buttons provided the user with several answer options ranging from a simple 'yes' or 'no' to more specific responses such as 'I already knew that' and 'I didn't know that yet'.

The chatbot conversations were based on the 5A's model as discussed in a toolkit produced by the WHO (2014) to aid primary care providers in delivering brief tobacco interventions. This model represents the five stages a brief smoking intervention should consist of: ask, advise, assess, assist and arrange. An example conversation of the chatbot in the personalisation/affective empathy condition can be found in Figures 1-9 (https://go.flow.ai/85xbG4Qrh). A full list of conversational topics can be found in Table 2.

Table 2.

Conversational topics used by the chatbot per stage of the 5A's model.

5A's stages	**Conversational topics**
Ask	Greeting, asking whether user smokes or not
Advise	Information about health
	(Gender-specific) information about health risks
	Reviewing financial situation
Assess	Asking the user whether they would be willing to quit
Assist	Providing smoking cessation strategies
	Advice on dealing with friends/family/colleagues who smoke
	Discussing coping strategies
	Discussing triggers and 4D's
	Nicotine Replacement Therapy (NRT)
Arrange	Information about additional help, asking about quitting attempt

Figure 1.

Example conversation in the personalisation/affective empathy condition: ask stage.

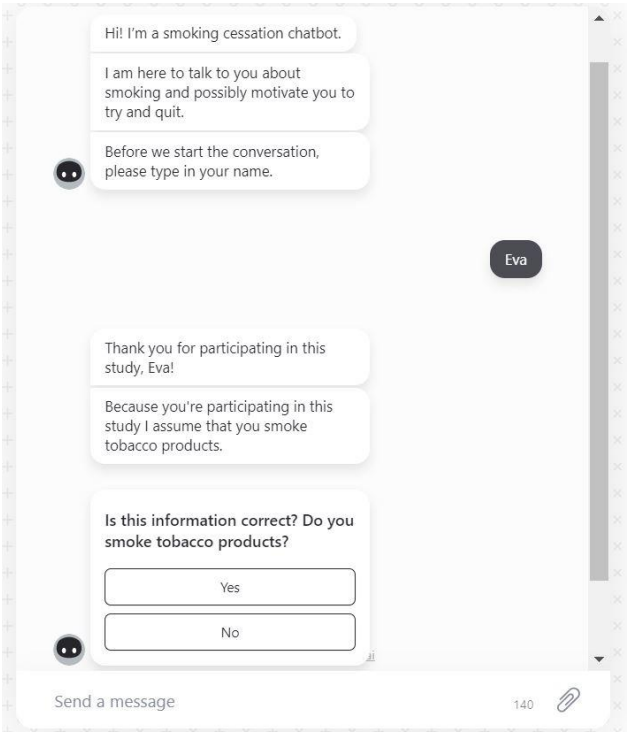


Figure 2.

Example conversation in the personalisation/affective empathy condition: advise stage, health risks.

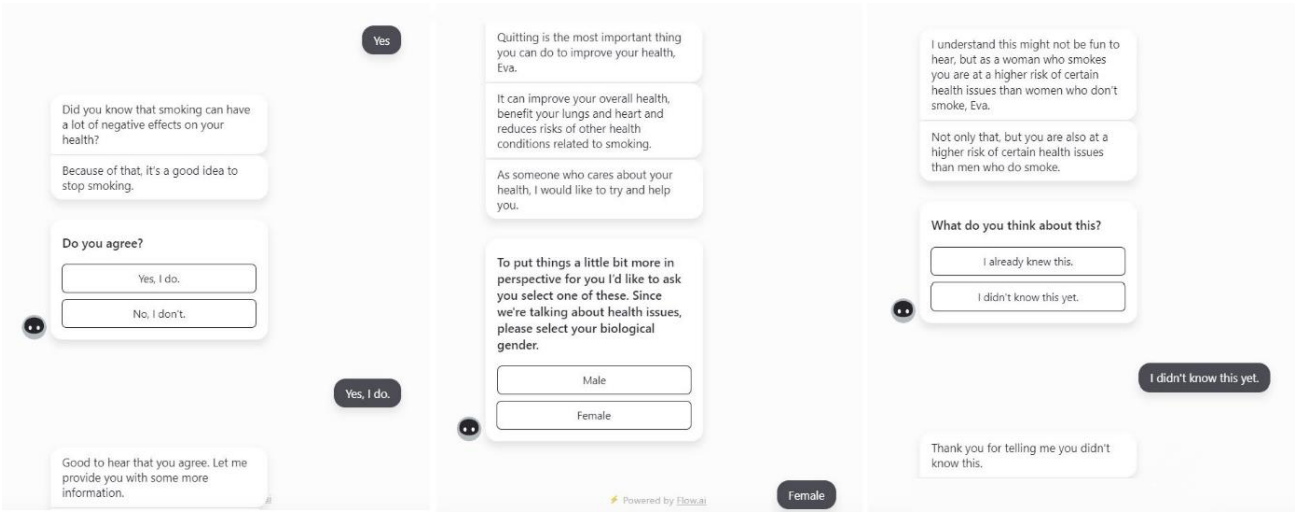


Figure 3.

Example conversation in the personalisation/affective empathy condition: advise stage, financial awareness.

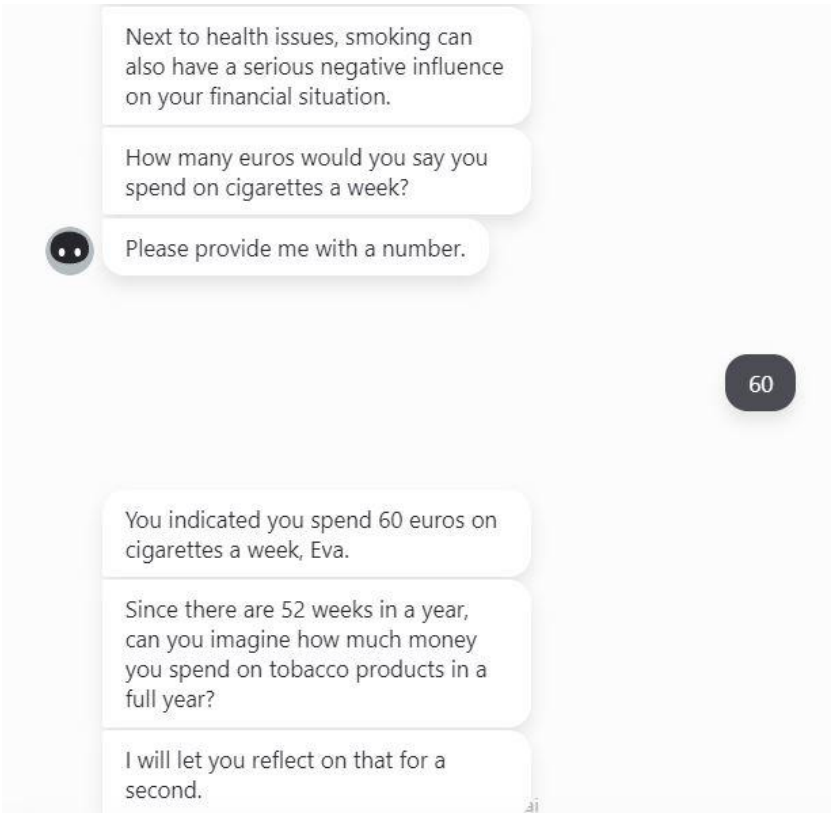


Figure 4.

Example conversation in the personalisation/affective empathy condition: assess stage.

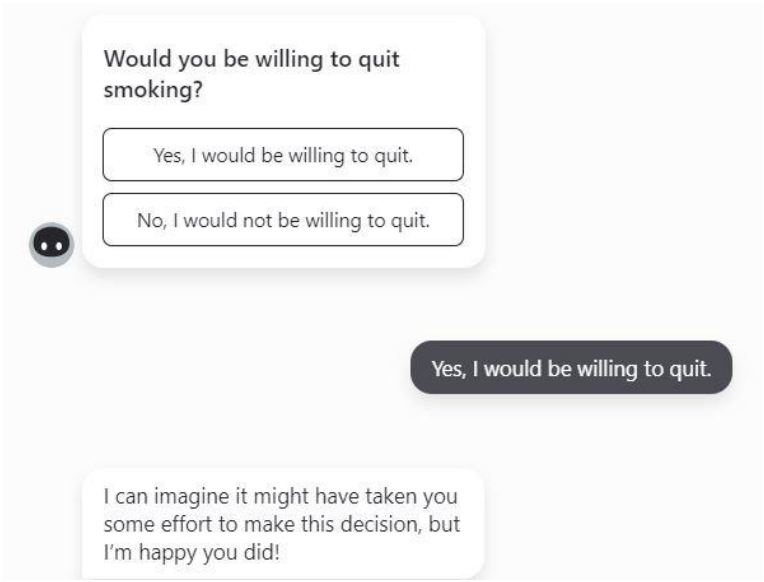


Figure 5.

Example conversation in the personalisation/affective empathy condition: assist stage, quitting strategies and advice on family/friends/colleagues who smoke.

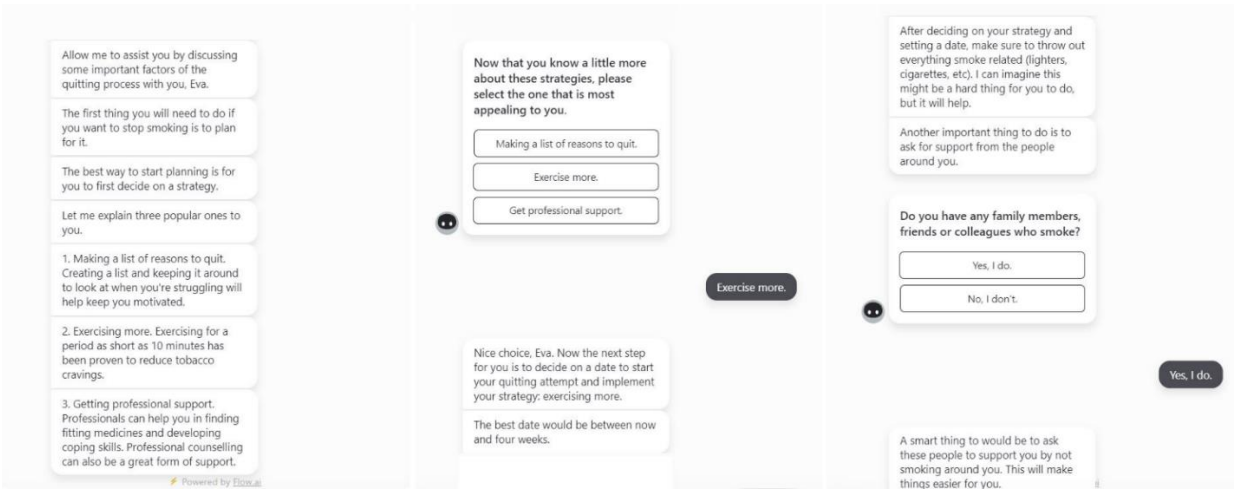


Figure 6.

Example conversation in the personalisation/affective empathy condition: assist stage, coping strategies.

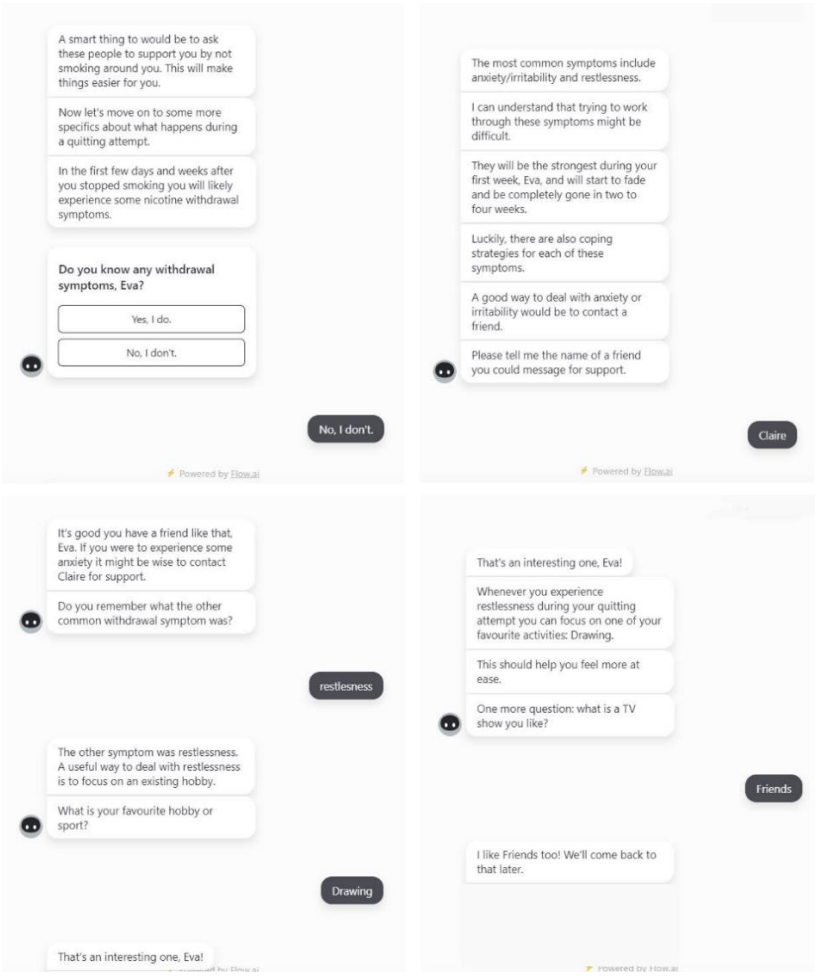


Figure 7.

Example conversation in the personalisation/affective empathy condition: assist stage, triggers and 4D's.

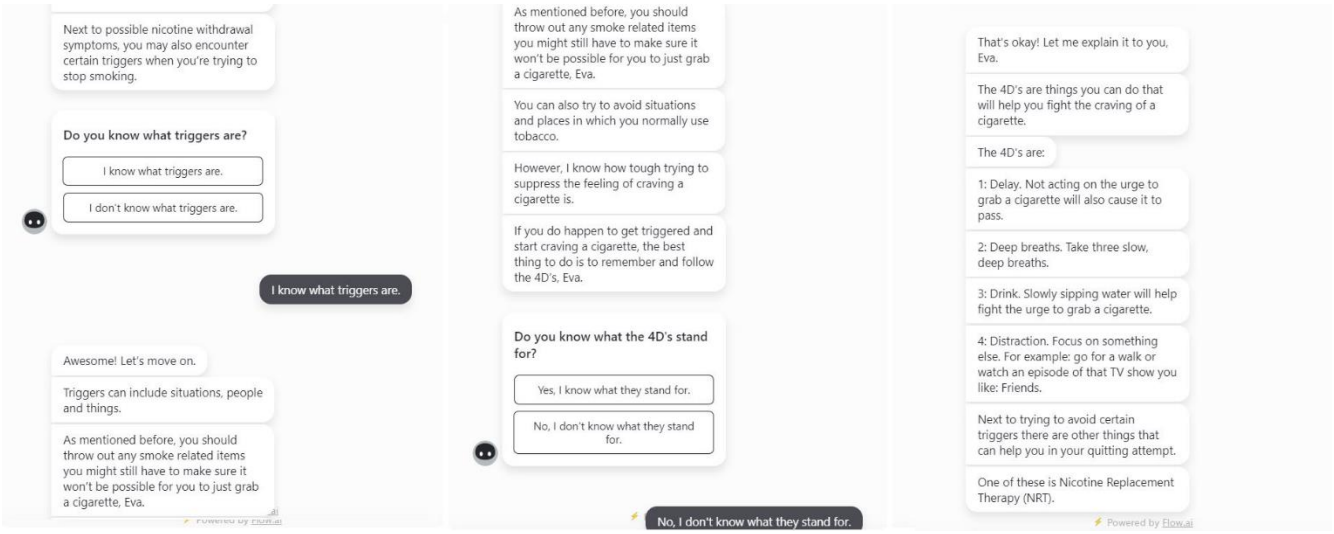


Figure 8.

Example conversation in the personalisation/affective empathy condition: assist stage, NRT.

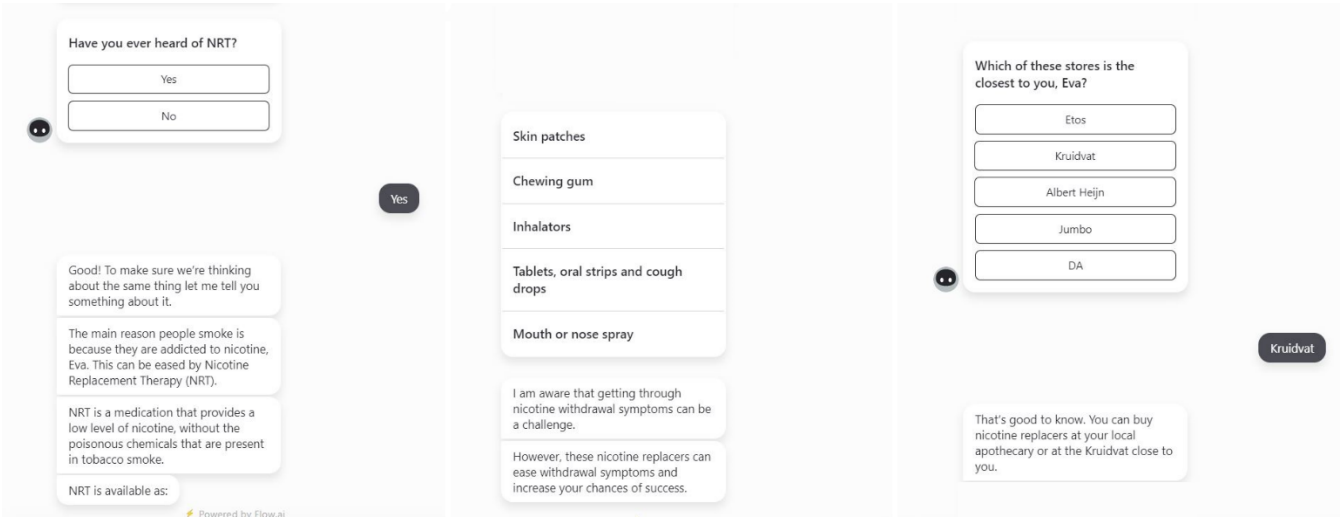
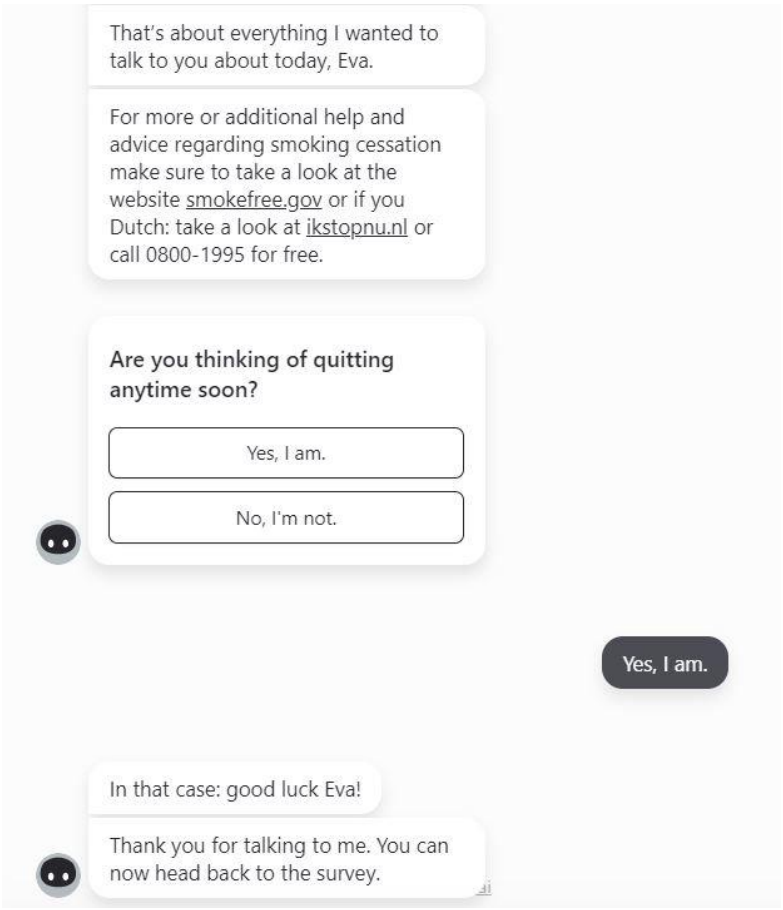


Figure 9.

Example conversation in the personalisation/affective empathy condition: arrange stage, end of conversation.



3.3.2 Manipulations

Empathy. The independent variables of this study have been manipulated as follows. For empathy, there were three different levels: no empathy, cognitive empathy and affective empathy. The manipulations of these three levels of empathy in the chatbot messages were based on those used by Liu and Sundar (2018).

In the no empathy conditions, the chatbots' messages included no expressions of empathy and little emotion. Instead, the chatbots simply provided the user with the questions, advice and information it had for them. An example of a message in all three empathy conditions can be found in Figure 10.

In the cognitive empathy conditions, the chatbots' messages included expressions that showed the user that the chatbot acknowledges their feelings. Furthermore, the cognitive empathy conditions also included some additional messages in comparison to the no empathy condition. An example of such an additional message for both the cognitive and the affective empathy conditions can be found in Figure 11.

In the affective empathy conditions, the chatbots' messages included expressions that showed the user that it not only acknowledged their feelings but understands those feelings and why the user could have been feeling them as well. Similar to the cognitive empathy condition, the affective empathy condition also included some additional messages in comparison to the no empathy condition.

Figure 10.

A message in respectively the affective empathy, cognitive empathy and no empathy conditions.

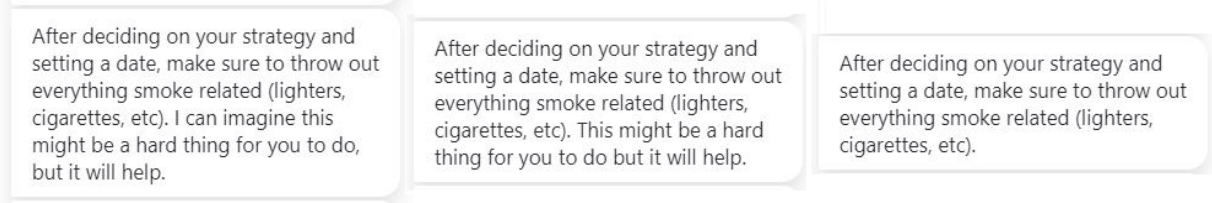
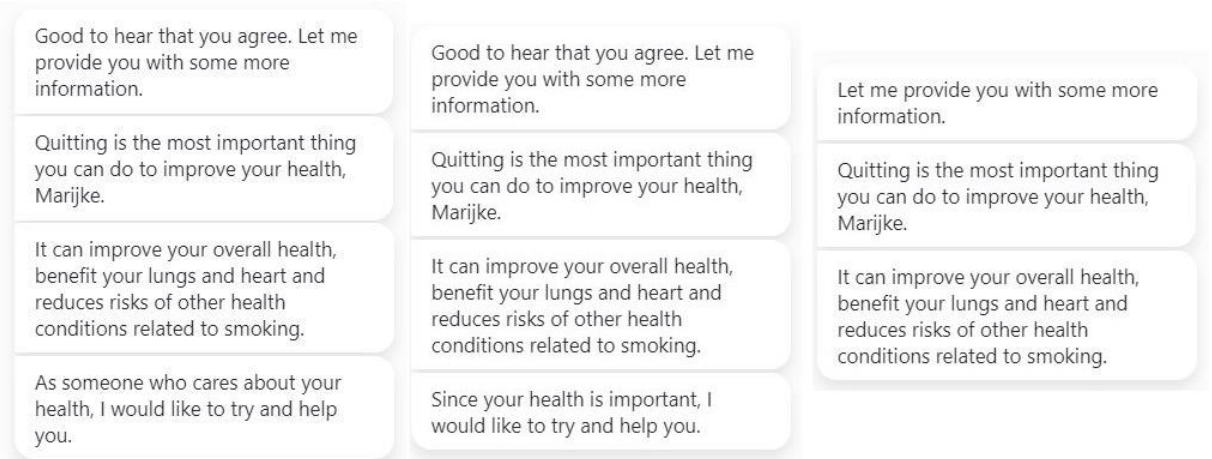


Figure 11.

Example of (additional) messages in respectively the affective empathy, cognitive empathy and no empathy conditions.

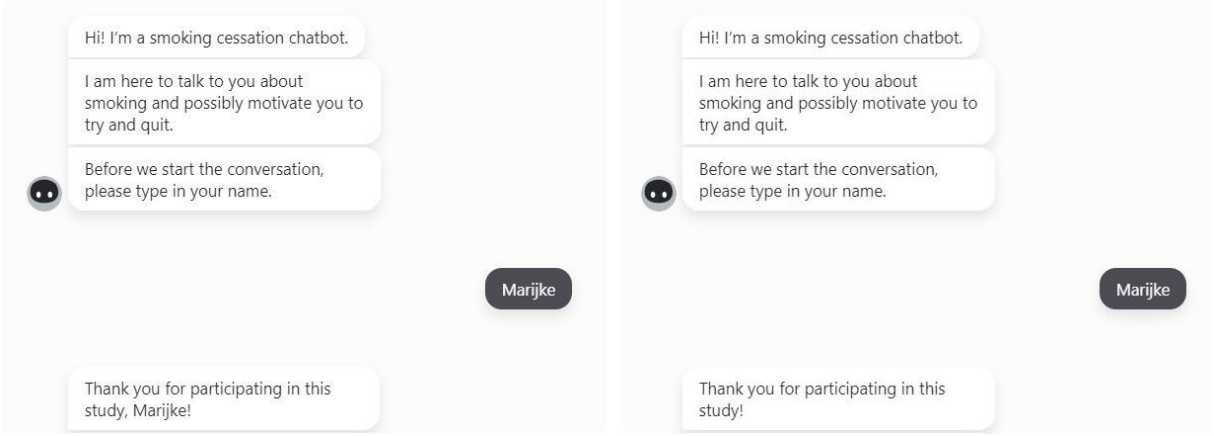


Personalisation. Personalisation was manipulated by personally addressing the user as well as asking them for specific information and using this information to personalise the chatbots' responses.

To personally address the user the chatbots were set up to ask the user for their name at the start of the conversation and then addressed them by their given name throughout the conversation. An example of a difference between the non-personalised chatbot conditions and the personalised chatbot conditions in regards to addressing the user by their name can be found at the start of the conversation, right after the user has typed in their name. This is shown in Figure 12. In the personalised conditions, the user's name was called upon a total of sixteen times throughout the conversation.

Figure 12.

Asking for input and addressing the user in the personalised and non-personalised conditions.



To personalise specific messages the conversational flow for all of the six chatbots included asking the users several questions throughout the conversation. In the non-personalised conditions, the chatbots asked questions and responded to the users' answers, but did not return any of the information the users had provided. In the personalised conditions, the chatbots did return some of the provided information. These questions included open-ended ones such as asking the users for their favourite hobby, their favourite TV series and the name of a supportive friend. An example of an open-ended question can be found in Figure 13.

Next to open-ended questions, the chatbot also used closed questions. Closed questions asked by the chatbot included whether the user was a tobacco smoker or not, whether they agreed with something, their gender, whether they already knew something, their willingness to quit and what store was closest to them.

The way the chatbots responded to these answers depended on which version of the chatbot was used. For example, when asked whether they already knew a provided fact or not the users could choose "*I already knew this*" or "*I didn't know this yet*" and the chatbot could either refer to that information or not depending on the experimental condition. An example of this is shown in Figure 14.

Figure 13.

Example of an open-ended question in a personalised and non-personalised condition.

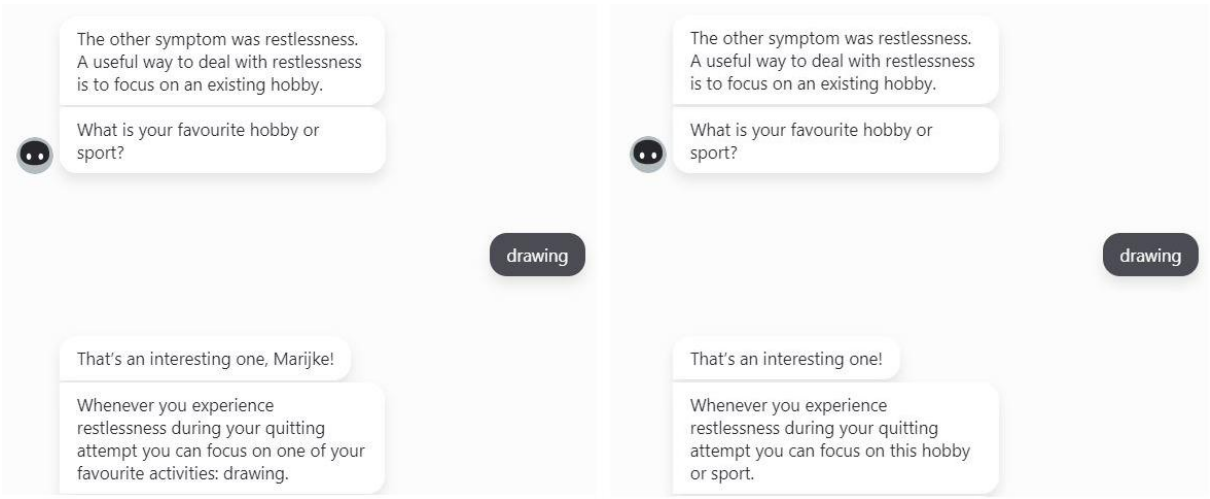
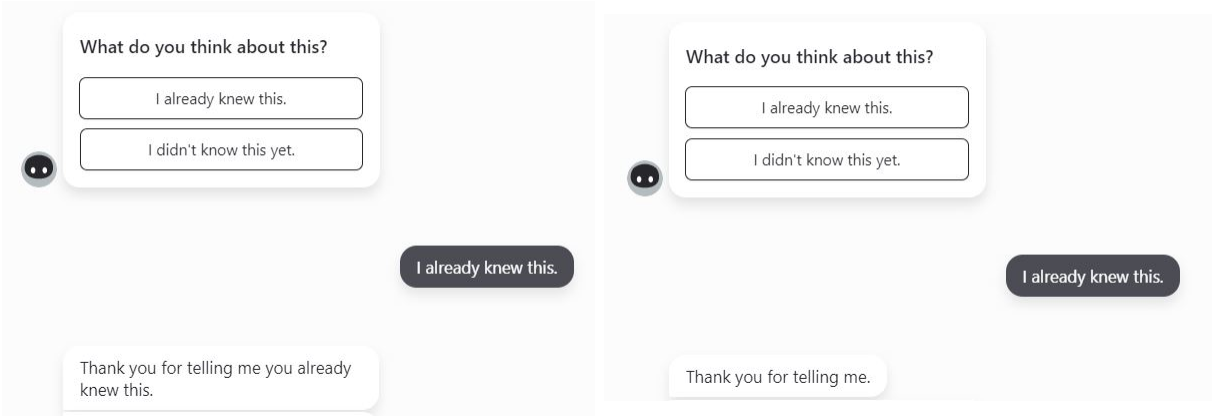


Figure 14.

Example of a closed question in a personalised and non-personalised condition.



3.3.3 Pre-test

Table 3.

Examples of changes in chatbot messages before and after pretest feedback.

Message before change	**Message after change**
Could you tell me your name?	Please type in your name.
What is your favourite hobby?	What is your favourite hobby or sport?
Could you also tell me the title of your favourite TV show?	One more question: what is a TV show you like?

To test whether the materials were manipulated the right way, a pre-test was conducted. This pre-test consisted of the questionnaire used in the original experiment with an additional question asking whether or not participants noticed any difficulties or things that did not seem right. A total of 21 participants took part in the pre-test. The feedback these participants gave and remarks they had about the survey or the chatbot served as input for changes made to the materials. This included some small typos in the chatbot conversations as well as one in the survey. Furthermore, the manipulation check questions showed that whilst the manipulations seemed to be working there was still room for improvement. Specifically, some messages in the two chatbot conditions that did not include empathy were altered to only relay information without involving emotion. For example, "*that's alright, let me explain it to you*" was changed to "*let me explain it to you*".

Another remark participants in the pre-test had was that when the chatbot asked them for their name they would respond with a full sentence, which in the personalised condition led to the chatbot storing the full sentence in the name parameter. Because of this, every time the chatbot needed to recall the user's name it would recall the entire sentence. To try and keep this from happening the message that asked users for their name was changed. A similar remark was given for the questions regarding a user's favourite hobby or TV show. In this case, participants would sometimes answer by typing in they did not have one which would cause the chatbot to save that sentence in the corresponding parameter. This was likely because whilst people may like to do something, they might not immediately call it a hobby. To try and prevent this from happening these messages have been changed by making them slightly more generic. A few clear changes are shown in Table 3.

3.4 Procedure

The data collection period for this study ran from the 17th of March 2021 until the 3rd of June 2021. The link to the survey was shared through various platforms in order to recruit participants and the recruitment message indicated that it would take participants around 15-20 minutes to finish the survey.

Once participants decided to take part in the study they would click the link in a message on one of the platforms mentioned above and would be taken to the survey. The full survey can be found in Appendix A. Here, they would first read the introduction text after which they would read the informed consent (Appendix B) and indicate whether or not they understood the terms of the study and agreed to participate. If participants did not agree to participate they would be referred to a message that told them they provided an answer that kept them from taking part in the study and thanked them for their time.

Participants who did agree to participate would then be asked the criteria check questions (i.e. “What is your age” and “Do you smoke tobacco products?”) , after which they would be asked to answer the demographic part of the survey as well as rate the items used to measure their previous chatbot experience (i.e. “I am familiar with chatbot technologies” and “I use chatbots frequently.”). Once they finished answering these questions participants would be provided with information about the study and what was expected of them. They were then provided with a link to one of the chatbots and asked to click the link to start the conversation. After finishing their conversation with one of the chatbots participants headed back to the survey where they were asked to fill in a number provided to them. This was a number ranging from 1-6 that was used to identify which version of the chatbot the participant had talked to. The chatbot conditions were randomly assigned and distributed by the Qualtrics software.

Moving on from the chatbot conversation participants arrived at the experimental questions part of the survey. They would rate the statements provided to them for all three dependent variables. After this, participants answered the manipulation check questions. Once this was done participants were provided with the opportunity to leave any remarks they had about the study and were debriefed upon completion (Appendix C).

3.5 Measures

Several variables were included in this study. Next to the demographic variables (age, gender, educational level, native English speaker yes/no) two other possible control variables were added: the number of cigarettes someone smokes on average per day and their prior chatbot experience. The number of cigarettes someone smokes was measured by asking them to fill in a number. Prior chatbot experience was measured using a scale (α = .74) derived from Ashktorab, Jain, Liao and Weisz (2019). This scale can be found in Table 4.

Table 4.

Items used to measure prior chatbot experience.

Item	Answer options
I am familiar with chatbot technologies.	1 = strongly disagree 7 = strongly agree
I use chatbots frequently.	1= strongly disagree 7 = strongly agree

3.5.1 Measures

The dependent variables measured in this study were satisfaction with the conversation, attitude towards using the chatbot and the intention to quit smoking.

Satisfaction with the conversation. Participants' satisfaction with the chatbot conversation was measured using a scale based on the one used by Barger and Grandey (2006). This scale consisted of three items on a 7-point Likert Scale (α = .89) ranging from 'extremely dissatisfied' to 'extremely satisfied'. The items have been adapted to fit the context of the chatbot. These adaptations were based on those of Verhagen, Van Nes, Feldberg and Van Dolen (2014), whose items were "*how satisfied are you with the virtual agent's advice*", "*how satisfied are you with the way the virtual agent treated you*" and "*how satisfied are you with the overall interaction with the virtual agent*". The adapted items used in this current study can be found in Table 5.

Table 5.

Items used to measure satisfaction with the conversation.

Item	Answer options
How satisfied are you with the chatbot's advice and information?	1 = extremely dissatisfied 7 = extremely satisfied
How satisfied are you with the way the chatbot treated you?	1 = extremely dissatisfied 7 = extremely satisfied
How satisfied are you with the overall interaction with the chatbot?	1 = extremely dissatisfied 7 = extremely satisfied

Attitude towards using the chatbot. Attitude towards using the chatbot was measured by using a scale derived from Moon and Kim (2000). This scale consisted of eight items: four positive ones and four negative ones (α = .93). These items were rated on a 7-point Likert Scale ranging from 'strongly disagree' to 'strongly agree'. The items were shown to the participants in random order by using the randomizer function provided by the Qualtrics software. These items can be found in Table 6.

Table 6.

Items used to measure attitude towards using the chatbot.

Item	Answer options
Using a chatbot for smoking cessation information and advice is a (good/bad) idea.	1 = strongly disagree 7 = strongly agree
Using a chatbot for smoking cessation information and advice is a (wise/foolish) idea.	1 = strongly disagree 7 = strongly agree
Using a chatbot for smoking cessation information and advice is a (pleasant/unpleasant) idea.	1 = strongly disagree 7 = strongly agree
Using a chatbot for smoking information cessation and advice is a (positive/negative) idea.	1 = strongly disagree 7 = strongly agree

Intention to quit smoking. Intention to quit smoking was measured using a scale derived from Rise, Kovac, Kraft and Moan (2008). This scale consisted of three items that had to be rated on a 7-point Likert Scale (α = .93). These items can be found in Table 7.

Table 7.

Items used to measure intention to quit smoking.

Survey item	Answer options
During the next 3-4 months I intent to quit smoking.	1 = very unlikely 7 = very likely
During the next 3-4 months I expect to quit smoking.	1 = very unlikely 7 = very likely
During the next 3-4 months I will try to quit smoking.	1 = very unlikely 7 = very likely

3.5.2 Manipulation measures

To test whether the manipulations of the dependent variables in this study worked well, manipulation check items were included for personalisation, cognitive empathy and affective empathy. Perceived personalisation was measured with three items derived from Maslowska, Smit and Van den Putte (2016). These items were originally focussed on a newsletter (e.g., "*was the newsletter targeted at you?*") and were adapted to fit the context of a chatbot. The items were rated on a 7-point Likert Scale (α = .86) ranging from 'strongly disagree' to 'strongly agree' and can be found in Table 8.

Perceived cognitive empathy was measured with three items on a 7-point Likert Scale (α = .90) and perceived affective empathy was measured with four items on a 7-point Likert Scale (α .86). Both scales ranged from 'strongly disagree' to 'strongly agree'. These items were created based on the manipulation of the two types of empathy in this study. The perceived empathy items can be found in Table 9.

Table 8.

Items used to measure perceived personalisation.

Item	Answer options
I felt like I was personally addressed by the chatbot.	1 = strongly disagree 7 = strongly agree
The chatbot was targeted at me.	1 = strongly disagree 7 = strongly agree
I recognized myself in the group the chatbot was targeted at.	1 = strongly disagree 7 = strongly agree

Table 9.

Items used to measure perceived cognitive (1,2) and affective (3-7) empathy.

Item	Answer options
1. The chatbot acknowledged emotions/feelings I might have.	1 = strongly disagree 7 = strongly agree
2. The chatbot tried to look at things from my perspective.	1 = strongly disagree 7 = strongly agree
3. The chatbot understood the emotions/feelings I might have.	1 = strongly disagree 7 = strongly agree
4. The chatbot cared about me.	1 = strongly disagree 7 = strongly agree
5. The chatbot showed concern for my well-being.	1 = strongly disagree 7 = strongly agree
6. The chatbot shared my emotions/feelings.	1 = strongly disagree 7 = strongly agree

4. Results

To test the effects of the use of empathy and personalisation by a smoking cessation chatbot on satisfaction with the conversation, attitude towards using the chatbot and intention to quit smoking several tests were performed including independent samples t-tests and Two-Way ANOVAs with post hoc Tukey HSD tests.

4.1 Analytical sample

At first, a total of 164 responses to the survey were recorded. Since Qualtrics was set to not save unfinished responses, all of these responses were coded as complete. However, five responses were removed because participants did not give their consent and were wrongfully saved as ‘complete’ responses. Another nine responses were manually filtered out and deleted because the time frame within which the survey was completed was below five minutes, which indicates that it was unlikely for the participants to have completed the entire chatbot conversation. This left 150 responses. To meet the number of participants suggested by the G*Power calculation an additional five participants were asked to complete the survey. This created an analytical sample of the 155 suggested participants.

Of this total number of participants, 23.9% was male (*N* = 37), 74.2% was female (*N*=115), 1.3% indicated to identify as other (*N* = 2) and one person indicated they preferred not to say. The average age of the participants was 25.11 (*SD* = 5.78, *MIN* = 19, *MAX* = 53). The other demographics can be found in Table 10. On average, participants scored prior chatbot experience between a 4 and a 5 (*M* = 4.81, *SD* = 1.45), meaning they had some experience but not a lot. Specifically, participants were slightly familiar with the existence of chatbot technologies (*M* = 4.99, *SD* = 1.64) but indicated not to use them on a frequent basis (*M* = 3.33, *SD* = 1.61). An overview of the conditions and the number of participants per condition can be found in Table 11, an overview of the numbers of participants per overarching group can be found in Table 12.

Table 10.

Participant demographics.

Demographic	**Type**	***Participants N (%)***
Smoker	Yes	44 (28.4%)
Smoker	No	111 (71.6%)
Native speaker	Yes	31 (20%)
Native speaker	No	124 (80%)
Education	High School	7 (4.5%)
Education	MBO (post-secondary vocational ed.)	4 (2.6%)
Education	HBO (university of applied sciences)	16 (10.3%)
Education	University Bachelor's Degree	68 (43.9%)
Education	University Master's Degree	58 (37.4%)
Education	PHD	2 (1.3%)

Table 11.

The six conditions used in this study with the corresponding number of participants per condition.

Condition	Empathy	Personalisation	Participants *N* (%)
1.	No empathy	No personalistion	22 (14.2%)
2.	No empathy	Personalisation	29 (18.7%)
3.	Cognitive empathy	No personalisation	23 (14.8%)
4.	Cognitive empathy	Personalisation	27 (17.4%)
5.	Affective empathy	No personalisation	28 (18.1%)
6.	Affective empathy	Personalisation	26 (16.8%)

Table 12.

Total number of participants per variable.

Variable	Participants *N (%)*
No personalisation	73 (47.1%)
Personalisation	82 (52.9%)
No empathy	51 (32.9%)
Cognitive empathy	50 (32.3%)
Affective empathy	54 (34.8%)

4.2 Manipulation and Randomization Checks

For this study, two independent variables were manipulated: the use of personalisation and the use of empathy. To check the manipulation of these two variables participants were asked to rate their chatbot conversation on perceived personalisation, perceived cognitive empathy and perceived affective empathy. Three different independent samples t-tests were run to perform the manipulation checks. The first t-test was performed with perceived personalisation as test variable and personalisation (yes/no) as grouping variable. On average, participants in the personalised conditions scored higher on perceived personalisation (M = 4.52, SD = 1.53) than participants in the non-personalised conditions (M = 4.30, SD = 1.41). This difference was not significant, $Mdif$ = .23, $t(153) = 00.96$, p = .341.

The second t-test was performed with perceived cognitive empathy as test variable and cognitive empathy (yes/no) as grouping variable. On average, participants in the cognitive empathy conditions (M = 4.40, SD = 1.43) and conditions without cognitive empathy (M = 4.39, SD = 1.53) scored more or less the same and there was no significant difference between the conditions, $Mdif$ = .01, $t(153)$ = .04, p = .970. A third t-test was performed with perceived affective empathy as test variable and affective empathy (yes/no) as grouping variable. On average, participants in the affective empathy condition scored slightly higher (M = 4.36, SD = 1.34) than participants in the conditions without affective empathy (M = 4.27, SD = 1.26). This difference was not significant, $Mdif$ = .08, $t(153)$ = .38, p = .699. The results of these manipulation checks show that the manipulations were not strong enough.

To check for randomization across conditions, One-Way ANOVAs with age, gender, smoker (yes/no), native English speaker (yes/no) and prior chatbot experience as dependent variables and personalisation and empathy as factors were performed. These tests showed no significant differences between the groups. The tables with results for each test can be found in Appendices D and E.

4.3 Hypotheses testing

To test H1-H5 three Two-Way ANOVA's were run with satisfaction, attitude and intention to quit smoking as dependent variables and personalisation and empathy as factors. A post hoc Tukey HSD test was conducted to assess the possible differences between the empathy conditions.

4.3.1 Effects on Satisfaction

To test H4a and H5 a Two-Way ANOVA with satisfaction as dependent variable was performed. Both the assumption of normality as well as the assumption of homogeneity of variances were met. The performed ANOVA showed no significant main effect for personalisation on satisfaction ($F(1, 149)$ = .51, p = .477, η^2 = .00) nor did it show a significant main effect for empathy ($F(2, 149)$ = 1.13, p = .326, $\eta 2$ = .01). There is also no significant interaction effect of personality and empathy on satisfaction ($F(2,149)$ = .78, p = .458, η^2 = .01) which indicated that H4a and H5a cannot be supported. These results are visualised in Figure 15. Although non-significant, the mean scores for each condition to show a trend where participants in the no empathy conditions were least satisfied with the conversation (Table 13).

The post hoc Tukey HSD test showed that there were no significant differences between no empathy and cognitive empathy (p = .448), no significant differences between no empathy and affective empathy (p = .412) and no significant differences between cognitive and affective empathy (p = .999) on satisfaction. Therefore, H1a, H2a and H3a could not be supported. The mean scores for each empathy type on satisfaction with the conversation can be found in Table 14.

Table 13.

Mean scores on satisfaction per condition.

Condition	**Mean**	**Standard Deviation**
No personalisation/No Empathy	M = 4.86	SD = 1.09
No personalisation/Cognitive Empathy	M = 5.46	SD = 1.15
No personalisation/Affective Empathy	M = 5.25	SD = 1.02
Personalisation/No empathy	M = 4.97	SD = 1.25
Personalisation/Cognitive Empathy	M = 5.00	SD = 1.25
Personalisation/Affective empathy	M = 5.19	SD = 1.28

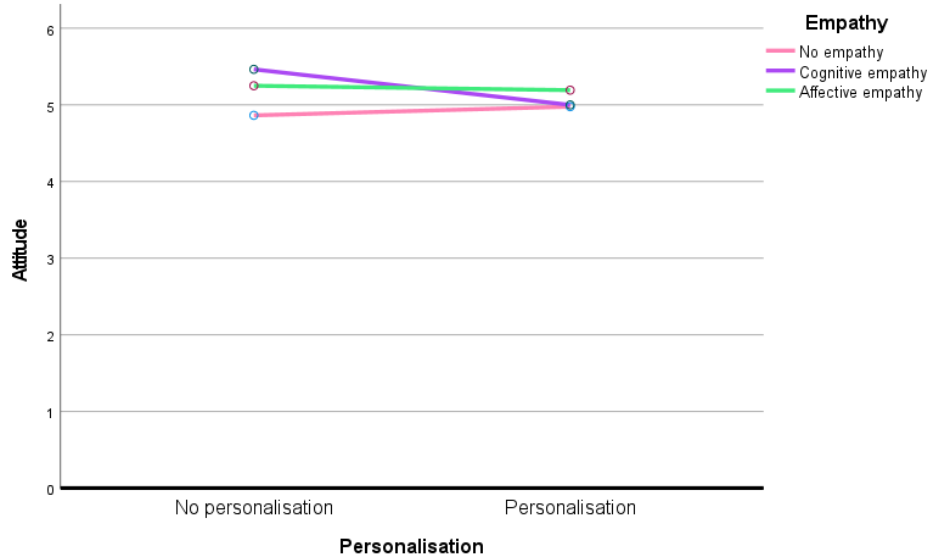
Table 14.

Mean scores on satisfaction per type of empathy.

Type of empathy	**Satisfaction**
No empathy	M = 4.93, SD = 1.17
Cognitive empathy	M = 5.21, SD = 1.22
Affective empathy	M = 5.22, SD = 1.15

Figure 15.

Mean scores of personalisation on satisfaction, separated by the level of empathy.



4.3.2 Effects on Attitude

To test H4b and H5b, a Two-Way ANOVA was performed with attitude as dependent variable. Both the assumption of normality as well as the assumption of homogeneity of variances were met. The performed ANOVA shows no significant main effect for personalisation on attitude ($F(1, 149) = 1.05$, $p = .306$, $\eta 2 = .01$) nor does it show a significant main effect for empathy on attitude ($F(2, 149) = .054$, $p = .947$, $\eta 2 = .00$). The results also show no significant interaction effect of personalisation and empathy on attitude ($F(2, 149) = 2.31$, $p = .103$, $\eta 2 = .03$), which indicates that H4b and H5b cannot be supported. These results have been visualised in Figure 16. Although the performed ANOVA shows no significant results there is a possible trend to be found in the interactions of empathy and personalisation.

Participants in the cognitive empathy/no personalisation condition reported a more positive attitude ($M = 5.39$, $SD = 0.81$) than participants in the cognitive empathy/personalisation condition ($M = 4.64$, $SD = 1.21$). For affective empathy, this trend seems to be the other way around. Participants in the affective empathy/no personalisation condition report a less positive attitude ($M = 4.88$, $SD = 1.12$) than those in the affective empathy/personalisation condition ($M = 5.04$, $SD = 1.26$). All mean scores on attitude per condition can be found in Table 15.

The post hoc Tukey HSD test showed that there were no significant differences between no empathy and cognitive empathy (p = .982), no significant differences between no empathy and affective empathy (p = .997) and no significant differences between cognitive and affective empathy (p = .994) on attitude towards the chatbot. Therefore, H1b, H2b and H3b could not be supported. The mean scores for each empathy type on attitude towards the conversation can be found in Table 16.

Table 15.

Mean scores on attitude scores condition.

Condition	**Mean**	**Standard Deviation**
No personalisation/No Empathy	M = 4.92	SD = 1.07
No personalisation/Cognitive Empathy	M = 5.39	SD = 0.81
No personalisation/Affective Empathy	M = 4.88	SD = 1.12
Personalisation/No empathy	M = 4.95	SD = 1.28
Personalisation/Cognitive Empathy	M = 4.64	SD = 1.21
Personalisation/Affective empathy	M = 5.04	SD = 1.26

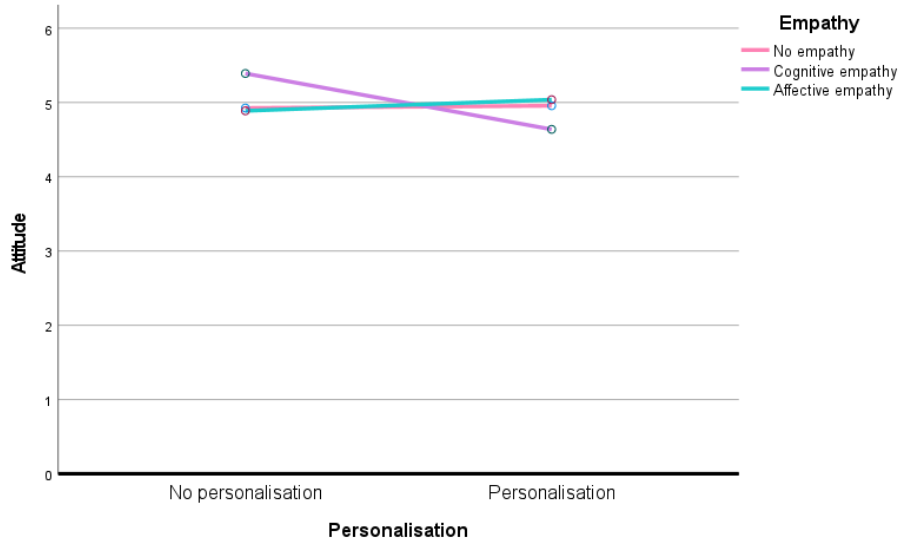
Table 16.

Mean scores on attitude per type of empathy.

Type of empathy	**Attitude**
No empathy	M = 4.94, SD = 1.19
Cognitive empathy	M = 4.99, SD = 1.10
Affective empathy	M = 4.96, SD = 1.18

Figure 16.

Mean scores of personalisation on attitude, separated by the level of empathy.



4.3.3 Effects on Intention to Quit Smoking

To test H4c and H5c, a Two-Way ANOVA with intention to quit smoking as dependent variable has been performed. Both the assumption of normality as well as the assumption of homogeneity of variances were met, although Levene's test was close to significance ($F(3, 151) = 2.62$, $p = .053$). The performed ANOVA shows no significant main effect of personalisation on intention to quit smoking ($F(1,149) = .59$, $p = .443$, $\eta 2 = .00$) nor does it show a significant main effect of empathy ($F(2, 149) = 1.89$, $p = .155$, $\eta 2 = .02$). The results also show no significant interaction effect of personalisation and empathy on intention to quit smoking ($F(2, 149) = 2.83$, $p = .061$, $\eta 2 = .03$), which indicates that H4c and H5c cannot be supported. These results have been visualised in Figure 17. Although the performed ANOVA showed no significant effects, it should be noticed that participants in the condition that included neither personalisation nor empathy rated intention to quit smoking lower ($M = 4.45$, $SD = 1.94$) than participants in all other conditions. An overview of the mean scores on intention to quit smoking per condition can be found in Table 17.

The post hoc Tukey HSD test showed that there were no significant differences between no empathy and cognitive empathy ($p = .793$), no significant differences between no empathy and affective empathy ($p = .160$) and no significant differences between cognitive and affective empathy ($p = .471$) on attitude towards the chatbot. Therefore, H1c, H2c and H3c could not be supported. The mean scores for each empathy type on intention to quit smoking can be found in Table 18.

Table 17.

Mean scores on intention to quit smoking per condition.

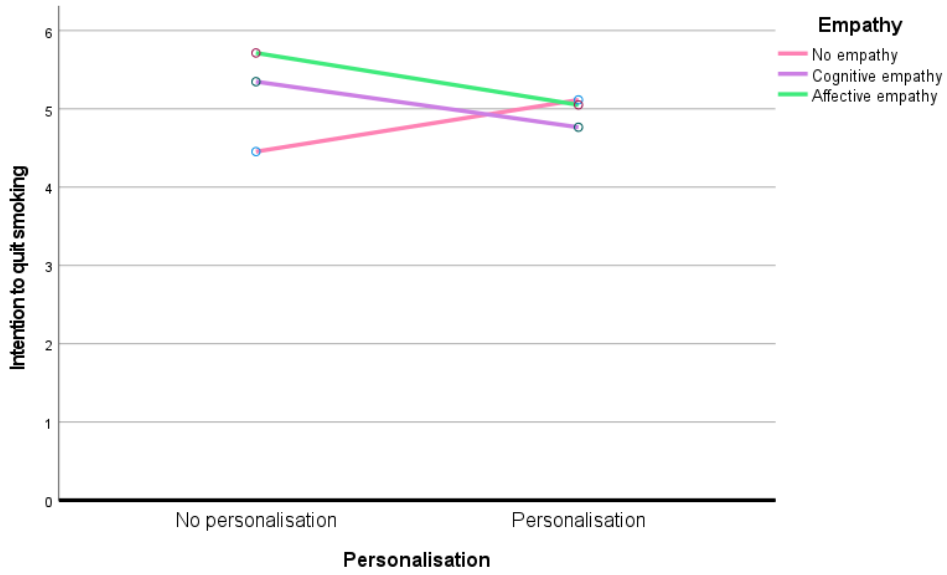
Condition	**Mean**	**Standard Deviation**
No personalisation/No Empathy	*M* = 4.45	*SD* = 1.94
No personalisation/Cognitive Empathy	*M* = 5.35	*SD* = 1.48
No personalisation/Affective Empathy	*M* = 5.71	*SD* = 1.21
Personalisation/No empathy	*M* = 5.11	*SD* = 1.61
Personalisation/Cognitive Empathy	*M* = 4.76	*SD* = 1.59
Personalisation/Affective empathy	*M* = 5.05	*SD* = 1.56

Table 18.

Mean scores on intention to quit smoking per type of empathy.

Type of empathy	**Attitude**
No empathy	*M* = 4.83, *SD* = 1.77
Cognitive empathy	*M* = 5.03, *SD* = 1.56
Affective empathy	*M* = 5.39, *SD* = 1.42

Figure 17.
Mean scores of personalisation on intention to quit smoking, separated by the level of empathy.



4.4 Additional analyses

Since this study was meant to focus on smokers rather than non-smokers, additional analyses were run to see whether there were differences between these groups. First of all, the possible difference in gender was analysed. The descriptives shown in Table 19 show that although there is a large difference between the number of participants that do and do not smoke, the ratios of males and females within these groups lie close together. The same goes for participants' educational levels, which can be found in Table 20. These descriptives show that the percentages of Bachelor and Master Degree students in the smoker and non-smoker groups lie close together. Table 21 shows the number of participants per group that indicated to be or not be a native English speaker. Finally, there was no remarkable difference between prior chatbot experience reported by smokers (M = 4.23, SD = 1.41) and non-smokers (M = 4.13, SD = 1.47).

Table 19.

Division of gender for smokers and non-smokers.

Gender	**Smoker**	**Non-smoker**
Male	12 (27.3%)	25 (22.5%)
Female	31 (70.5%)	84 (75.7%)

Table 20.

Division of educational levels for smokers and non-smokers.

Educational level	**Smoker**	**Non-smoker**
High school	3 (6.8%)	4 (3.6%)
MBO (post-secondary vocational education)	3 (6.8%)	1 (.9%)
HBO (university of applied sciences)	4 (9.1%)	12 (10.8%)
University Bachelor's Degree	18 (40.9%)	50 (45%)
Univeristy Master's Degree	15 (34.1%)	43 (38.7%)
PHD	1 (2.3%)	1 (.9%)

Table 21.

Division of gender for smokers and non-smokers.

Native English Speaker	**Smoker**	**Non-smoker**
Native speaker	10 (22.7%)	21 (18.9%)
Non-native speaker	34 (77.3%)	90 (81.1%)

To further look into the possible differences between smokers and non-smokers, a One-Way ANOVA was performed to investigate whether there were differences in the outcome variables for smokers and non-smokers. Since the sample sizes of these groups were unequal, the Welch statistic will be reported. The results showed that there was no significant difference between smokers and non-smokers on attitude ($F(2, 153) = 1.55$, $p = .298$) or satisfaction ($F(1, 153) = 3.56$, $p = .068$). The results did indicate a significant difference between smokers and non-smokers on intention to quit smoking, $F(1, 153) = 14.21$, $p = .002$. This effect showed that non-smokers who were pretending to be smokers reported a higher intention to quit smoking than actual smokers did. The mean scores for smokers and non-smokers on the dependent variables are shown in Table 22.

Table 22.

Mean scores on the dependent variables for smokers and non-smokers.

Smoker (yes/no)	**Satisfaction**	**Attitude**	**Intention to quit**
Smokers	$M = 4.84$, $SD = 1.21$	$M = 4.80$, $SD = 1.21$	$M = 4.36$, $SD = 1.90$
Non-smokers	$M = 5.23$, $SD = 1.15$	$M = 5.03$, $SD = 1.13$	$M = 5.38$, $SD = 1.39$

5. Discussion

The goal of this study was to investigate the possible effects of implementing empathy and personalization into an e-health chatbot developed to provide users with smoking cessation information and advice in the form of a brief chatbot conversation. The first goal of the study was to fill the gap in the current literature by looking at what effects cognitive and affective empathy might have on satisfaction with the conversation, attitude towards using the chatbot and intention to quit smoking. The second goal was to find out what effects personalisation of the chatbot's messages might have on satisfaction with the interaction, attitude towards using the chatbot and intention to quit smoking. To achieve these goals six different versions of the same chatbot were developed and data was gathered regarding users' opinions about these chatbots.

5.1 Discussion of Results

The first three hypotheses of this study, H1(abc), H2(abc) and H3(abc), were formulated based on several other studies that showed that the use of empathy in smoking cessation interventions could have a positive effect on satisfaction, attitude and intention to quit smoking. Although studies by Ellis et al. (2007) and Shen (2011) showed positive effects of implementing empathy in interventions, the results of the current study cannot support this as no significant effect of empathy on the outcome variables was found. Furthermore, Liu and Sundar (2018) found that there was a difference in perception of an e-health chatbot when it used cognitive or affective empathy. The results of this current study did not find any evidence to support these findings. This means that H1(abc), H2(abc) and H3(abc) could not be supported. A reason for this could be that a chatbot using empathy might make some people feel uncomfortable because they do not believe it can actually feel emotions (Liu & Sundar, 2019).

Although there were no significant differences between the empathy conditions, it is worthwhile to notice that there was still a visible trend in the reported scores for satisfaction and intention to quit smoking. This trend showed that participants in the affective empathy conditions reported the highest scores, followed by those in the cognitive empathy conditions. Those in the no empathy conditions scored the lowest. This shows that even when the manipulations were weak, there are still differences to be observed. There was almost no difference in reported scores on attitude, which goes against the findings of Liu and Sundar (2018) that affective empathy should lead to more positive attitudes.

One explanation for this could be that, in general, participants reported a low score on the survey item about having frequently used chatbots before. This could indicate that they were simply not used to talking to a chatbot and therefore were unsure how to feel about it. Another possible explanation could be that participants felt indifferent towards the chatbot because they found it difficult to form an opinion about whether or not such a technology should be used in healthcare. Especially since the majority of participants did not smoke themselves.

H4(abc) was formulated based on several studies that showed positive effects of using personalisation in e-health interventions and chatbots. Studies by Dijkstra and Ballast (2012) and Kadariya et al. (2019) showed positive results for implementing personalisation in e-health interventions. The results of the current study, however, cannot support these previous findings and H4(abc) could not be supported. Pereira and Diaz (2019) mention both anonymity and personalisation as benefits of using chatbots in e-health, however, there is some disclarity in whether these factors work together or separately. This could possibly explain the lack of effects of personalisation on the outcome variables.

H5(abc) was formulated to investigate the possible interaction effects between personalisation and empathy. Pereira and Diaz (2019) mention that combining empathy and personalisation aspects in an e-health chatbot can lead to better outcomes on factors such as satisfaction. The results of the current study cannot confirm this, nor could they support H5(abc). A possible explanation for this could be the weakness of the manipulations, which did not work the way they were intended to. Another possible explanation could be the fact that it is difficult to emphasize with someone without personally addressing them, which suggests that empathy and personalisation might be more intertwined and fully separating them could be challenging.

Although none of the current study's hypotheses could be supported, there are some interesting findings still to notice. First of all, the p-value of the interaction between personalisation and empathy on intention to quit smoking seemed to be approaching significance (i.e. $p = .061$). This is interesting because it suggests that there could be an interaction effect between these two variables. When looking at what this effect might be the results indicate a difference in how the types of empathy interact with personalisation. For satisfaction and attitude, no empathy and affective empathy seem to have a positive interaction with personalisation, whereas cognitive empathy has a more negative interaction. An explanation for this could be that affective empathy might be more compatible with personalisation than cognitive empathy.

Liu and Sundar (2018) mention that cognitive empathy might sound more detached, which might have made combining it with personalisation feel unnatural to participants.

Additional analyses on the possible differences between smokers and non-smokers show that even though the non-smokers' group is larger, the demographics of these two groups are quite evenly distributed. The most important thing to note from these additional analyses is the significant difference between smokers and non-smokers on intention to quit smoking. The results showed that non-smokers reported a significantly higher intention to quit smokers than the actual smokers did. A possible explanation for this could be that smoking is in fact an addition, which might have made pretending to be a smoker a difficult situation. Furthermore, pretending to be a smoker might have caused participants to respond in more socially desirable ways, which might be the reason they reported higher scores for intention to quit smoking.

A final noticeable finding is that the mean scores reported by smokers on the outcome variables were all between a four and a five. This indicates that smokers did not specifically agree nor disagree with the items. This could mean that perhaps smokers are indifferent to using chatbot technologies for smoking interventions, which could indicate that using chatbots as e-health interventions for changing health behaviours might not be useful. It could also mean that smokers felt indifferent about the chatbot because it provided them with information they likely all had heard before, which made the entire conversation less interesting for them.

5.2 Theoretical and Practical Implications

Based on the results of this study several implications for the use of chatbots as e-health interventions can be made. A first theoretical implication is that when looking at the use of empathy in e-health interventions it is important to make a distinction between cognitive and affective empathy. Even though the results of this current study did not show significant differences between these types of empathy, there were visible trends that suggested that there could be a difference in how these types of empathy are perceived. Furthermore, multiple studies have mentioned that empathy should not be considered as a single conduct (Cuff et al., 2016; Shamay-Tsoory, Aharon-Perets & Perry, 2009) and yet there is still little research, especially in the field of e-health, that differentiates between the two types of empathy.

Another theoretical implication that can be made is that personalisation and empathy could be strongly linked together, which might make it difficult to separate the two. It seems nearly impossible for a chatbot to express empathy in its messages without also personalising a message to fit the user.

This relates to the results of this study, which could not support any of the hypotheses based on previous studies and showed no significant differences between any of the conditions.

This raises the question if e-health chatbots are generally perceived as personal or/and empathic. Even without manipulating personalisation in an e-health chatbot, the fact remains that when a user talks to a chatbot it becomes a one-on-one conversation, which means the conversation is focussed specifically on the user and their needs. This could invoke a feeling of perceived personalisation without intending to do so. The results of this current study support this, because even though the manipulations did not work all means were on the positive side of the scoring scales. Furthermore, the main focus of e-health chatbots is to either help a patient stay in touch, monitor their health or help them understand certain health issues and motivate them to change their unhealthy behaviours (Bates, 2019; Denecke et al., 2019; Peirera & Diaz, 2019). This, in turn, could cause users to perceive an e-health chatbot as empathic without any type of empathy manipulation, simply because the focus of such a chatbot is to aid that specific user.

A practical implication for developers working on e-health chatbots would be to work with actual physicians in creating such chatbots. The chatbots for the current study was created based on the 5A's model. Users were provided with a basic conversation that included limited information, advice and questions based on this model. Working with physicians in creating a chatbot to provide smoking cessation interventions could create more detailed, patient-focussed and in general better personalised chatbots which could be a useful tool in providing people with smoking cessation information and advice and possibly support them during a quitting attempt.

Another practical implication is that when developing an e-health chatbot it would be useful to implement empathy in the chatbot, preferably affective empathy. Although the results of the current study were not significant, it did show that participants in the affective empathy conditions scored higher on satisfaction with the conversation, attitude towards using the chatbot and intention to quit smoking than those in the cognitive empathy and no empathy conditions. This is in line with Liu and Sundar (2018), who did find significant differences between no empathy, cognitive empathy and affective empathy, with the latter resulting in more positive evaluations and an increased feeling of support.

5.3 Limitations and Suggestions

The current study focussed on the use of a chatbot as a possible smoking cessation intervention and contributes to a still growing field of research. There are some limitations and suggestions that need to be taken into account for further research. First of all, the present study only consisted of a small analytical sample which makes the results less generalizable. Nevertheless, the results of this study, albeit non-significant, did show some interesting differences between the experimental groups and possible interactions between personalisation and empathy. Therefore, it is important for future research to attempt to gather a larger analytical sample to see if that will create a more generalizable analytical sample.

Another limitation of the current study is that the majority of the participants did not smoke and therefore had to try and imagine a hypothetical situation in which they did smoke. However, since smoking is an addiction it might have been difficult for non-smokers to fully imagine what things would be like if they were in fact a smoker.

It might also have lead to participants filling in more socially acceptable answers, as one participant also commented after finishing the study. This is likely the reason why non-smokers resulted in having scored the intention to quit smoking items higher than actual smokers had. Future research should either try to create a sample that exists solely of smokers or a sample that has a better divide between smokers and non-smokers to evaluate the possible differences between those groups in a larger analytical sample.

A third limitation, which can be linked to the implications, is that the manipulation checks for this study showed that the manipulations did not seem to be working as well as they should. There are several factors that could have influenced this. Firstly, the fact that the idea of talking to a chatbot, in general, might have already influenced participants' feelings of perceived personalisation. Secondly, since the aim of the conversation was to help and inform the user this might have influenced perceived cognitive and affective empathy in a way that the general idea of the conversation could have lead to the chatbot being perceived as empathic. On that account, the chatbot conversations in the non-personalised conditions might have been perceived as personalised and the conversations in the no empathy conditions might have been perceived as empathic. Future research should build on this by focussing on the differences in chatbot perception.

6. Conclusion

The results of this study showed no statistically significant effects of the use of personalisation and empathy by a smoking cessation chatbot on satisfaction with the conversation, attitude towards using the chatbot and intention to quit smoking. Whilst there were no significant differences, the results of the study did show an increase in scores on satisfaction and intention to quit smoking between the no empathy, cognitive empathy and affective empathy conditions which could be further explored in larger samples consisting of smokers only. There were also no distinct differences between the personalised and non-personalised conditions. Since the majority of this study's participants consisted of non-smokers who had to imagine a hypothetical situation in which they did smoke, the results should be interpreted with care. Since none of the hypotheses from this study could be supported, the research question can be answered by saying that the use of personalisation and empathy by the smoking cessation chatbot had no effect on satisfaction with the conversation, attitude towards using the chatbot and intention to quit smoking. The main thing to take away from this study is the fact that even with weak manipulations all mean scores were still high. This suggests that chatbots might be perceived as personal and/or empathic by default, which should be taken into account by chatbot developers, especially within the field of e-health, and for any future research.

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Appendices

Appendix A.

Survey used for this study.

Dear participant,

First of all, I would like to thank you for taking the time to participate in this study. The purpose of this study is to look at certain design features that can be effective in creating a chatbot that can help people with the process of trying to quit smoking.

Participating in this study will take you about 15/20 minutes. During this time you will be asked some questions about yourself, after which you will be linked to the chatbot to engage in conversation. This conversation will take approximately 10 minutes. Once the conversation is finished you will be asked to answer some questions regarding the conversation. Both this survey as well as the chatbot conversation will be in English.

Your participation in this study is completely voluntary and you are free to quit at any time without having to provide an explanation. Your responses to this survey will be anonymous and the data gathered will be treated confidentially. The data will be stored in Tilburg University's database for a period of ten years. Please note that there will be no data gathered from the chatbot conversation. Any information you decide to share with the chatbot will be saved in the program for 24 hours and will then be automatically removed. The researcher has no access to these conversations.

Please note: the survey and the chatbot can be opened on a mobile phone, but work best on a computer/laptop.

This study is carried out for my Master's Thesis at Tilburg University. For any more information or questions regarding the study please contact me via m.i.fioole@tilburguniversity.edu.

Thank you in advance for taking the time to help me with this research,
Marijke Fioole

By proceeding with this research, you declare that you have read the information about the research, have the opportunity to ask questions and agree to the terms of this study.

In doing so, you acknowledge the following:

- I am aware that my participation in this study is completely voluntary.
- I am aware that I can opt out of this study at any given time without negative consequences and without providing an explanation.
- I am aware that my responses to this survey and the data collected from those will be anonymous.
- I am aware that the data collected from this survey will be treated confidentially.
- I am aware that the data collected from this survey will be stored in Tilburg University's database for a period of ten years.
- I am aware that the researcher will not obtain any information I share with the chatbot.
- I am aware that the information I share with the chatbot will be automatically deleted from the system after 24 hours.
- I am aware that the data gathered from this survey will be used for scientific research and resulting publications.

After being made aware of the abovementioned information, do you agree to participate in this study?

○ Yes, I agree to participate in this study.

○ No, I do not agree to participate in this study.

I'd like to start by asking you the following two questions.

What is you age? _____

Do you smoke tobacco product?

○ Yes, I smoke.

○ No, I do not smoke.

We will now move on with some questions about you. Please answer the following questions.

What is your gender?

- ○ Male
- ○ Female
- ○ Other
- ○ I prefer not to say

What is your highest current or completed level of education?

- ○ High school
- ○ MBO
- ○ HBO
- ○ Bachelor's degree
- ○ Master's degree
- ○ PHD
- ○ Other, namely: _____

Is English your first language?

- ○ Yes
- ○ No

On average, how many cigarettes do you smoke per day? If you do not smoke daily, fill in the number of cigarettes of a day that you do smoke. If you do not smoke at all, please enter '0'. Please answer using numbers only (e.g. 10).

_____

The next two items are about your prior experience with chatbots. Please indicate how much you agree with the following statements:

	Strongly disagree	Disagree	Somewhat disagree	Neither agree nor disagree	Somewhat agree	Agree	Strongly agree
I am familiar with chatbot technologies.	○	○	○	○	○	○	○
I use chatbots frequently.	○	○	○	○	○	○	○

In the following part of the survey you will be directed to the chatbot. Before you continue I would like to ask you to do two things:

- Please finish the **entire** chatbot conversation before moving on with the survey.
- **If you do not smoke please try your best to pretend that you are a smoker from now on.** Make sure to keep this in mind and try to imagine that you **do** smoke cigarettes when talking to the chatbot and fill out the rest of the survey since there might be some messages and questions related to this.

Thank you.

Please select what applies to you (if you are a smoker, please select 'I understand').

○ I understand and will imagine I am a smoker for the remainder of the experiment.

○ I do not understand and will not imagine I am a smoker for the remainder of the experiment.

We will now start with the experiment. For this experiment a chatbot has been designed that provides advice about smoking cessation*. A link to the chatbot can be found below. For the sake of the study I would like to ask you to finish the entire conversation with the chatbot. This conversation will take approximately ten minutes.

Clicking the link to the chatbot will open a new tab in your browser, in which you will be able to talk to the chatbot.

Please make sure you do **not** close this survey as you will need to return to it once you have finished your conversation with the chatbot.

Click here to start your chatbot conversation: let's talk!

* cessation = to quit

Thank you for returning to the survey. On the next page, please fill in the following number: **(1-6).**

Please write down the number that has just been shown to you: _____

The following questions will ask you about your opinions on the interaction you had with the chatbot.

Please indicate how satisfied you were with:

	Extremely dissatisfied	Dissatisfied	Slightly dissatisfied	Neither satisfied nor dissatisfied	Slightly satisfied	Satisfied	Extremely satisfied
The chatbot's advice and information.	○	○	○	○	○	○	○
The way the chatbot treated you.	○	○	○	○	○	○	○
Your overall interaction with the chatbot.	○	○	○	○	○	○	○

These next item will be about your attitude towards the use of the chatbot. Please indicate how much you agree with the following:

	Strongly disagree (1)	Disagree (2)	Slightly Disagree (3)	Neither agree nor disagree (4)	Slightly agree (5)	Agree (6)	Strongly agree (7)
Using a chatbot as a source of smoking cessation information is a good idea. (1)	○	○	○	○	○	○	○
Using a chatbot as a source of smoking cessation information is a bad idea. (2)	○	○	○	○	○	○	○
Using a chatbot as a source of smoking cessation information is a wise idea. (3)	○	○	○	○	○	○	○
Using a chatbot as a source of smoking cessation information is a foolish idea. (4)	○	○	○	○	○	○	○
Using a chatbot as a source of smoking cessation information is a pleasant idea. (5)	○	○	○	○	○	○	○
Using a chatbot as a source of smoking cessation information is an unpleasant idea. (6)	○	○	○	○	○	○	○
Using a chatbot as a source of smoking cessation information is a positive idea. (8)	○	○	○	○	○	○	○

Using a chatbot as a source of smoking cessation information is a negative idea. (9)	○	○	○	○	○	○	○

The next three items will ask you about your intention to quit smoking. Please indicate how likely the following statements are:

	Very unlikely	Unlikely	Slightly unlikely	Neither likely nor unlikely	Slightly likely	Likely	Very likely
In the next 3-4 months I intent to quit smoking.	○	○	○	○	○	○	○
In the next 3-4 months I expect to quit smoking.	○	○	○	○	○	○	○
In the next 3-4 months I will try to quit smoking.	○	○	○	○	○	○	○

The next items will be about how personal you perceived the chatbot to be. Please indicate how much you agree with the following statements:

	Strongly disagree	Disagree	Somewhat disagree	Neither agree nor disagree	Somewhat agree	Agree	Strongly agree
I felt like I was personally addressed by the chatbot.	○	○	○	○	○	○	○
The chatbot was targeted at me.	○	○	○	○	○	○	○
I recognized myself in the group the chatbot was targeted at.	○	○	○	○	○	○	○

The following statements will ask you about how empathic you thought the chatbot was.

Please indicate how much you agree with the following:

	Strongly disagree	Disagree	Slightly disagree	Neither agree nor disagree	Slightly agree	Agree	Strongly agree
The chatbot acknowledged emotions/feelings I might have.	○	○	○	○	○	○	○
The chatbot tried to look at things from my perspective.	○	○	○	○	○	○	○
The chatbot recognized emotions/feelings I might have.	○	○	○	○	○	○	○

Please indicate how much you agree with the following:

	Strongly disagree	Disagree	Slightly disagree	Neither agree nor disagree	Slightly agree	Agree	Strongly agree
The chatbot understood the emotions/feelings I might have.	○	○	○	○	○	○	○
The chatbot cared about me.	○	○	○	○	○	○	○
The chatbot showed concern for my well-being.	○	○	○	○	○	○	○
The chatbot shared my emotions/feelings.	○	○	○	○	○	○	○

This final question is about the control you felt you had over the conversation. Please indicate how much you agree with the following:

	Strongly disagree	Disagree	Slightly disagree	Neither agree nor disagree	Slightly agree	Agree	Strongly agree
I was able to control the course of the conversation.	○	○	○	○	○	○	○
The conversation with the chatbot proceeded fluently.	○	○	○	○	○	○	○

If you have any remarks about this study, please indicate them here.

_____

Appendix B

Informed consent form.

By proceeding with this research, you declare that you have read the information about the research, have the opportunity to ask questions and agree to the terms of this study.

In doing so, you acknowledge the following:

- I am aware that my participation in this study is completely voluntary.
- I am aware that I can opt out of this study at any given time without negative consequences and without providing an explanation.
- I am aware that my responses to this survey and the data collected from those will be anonymous.
- I am aware that the data collected from this survey will be treated confidentially.
- I am aware that the data collected from this survey will be stored in Tilburg University's database for a period of ten years.
- I am aware that the researcher will not obtain any information I share with the chatbot.
- I am aware that the information I share with the chatbot will be automatically deleted from the system after 24 hours.
- I am aware that the data gathered from this survey will be used for scientific research and resulting publications.

After being made aware of the abovementioned information, do you agree to participate in this study?

○ Yes, I agree to participate in this study.

○ No, I do not agree to participate in this study.

Appendix C

Debriefing.

Thank you for taking the time to participate in this study. The aim of this study is to explore the use of relational behaviours by a chatbot that has been designed to help people in the process of quitting smoking. The relational behaviours used in this study were empathy and personalisation.

The chatbot you interacted with was specially designed for this study. The conversational topics, their order and all of the information provided by the chatbot are based on scientific sources and information provided by health services.

For more information or any questions about the study please feel free to contact me via m.i.fioole@tilburguniversity.edu.

Thank you again for your participation in this study.

Kind regards,
Marijke Fioole.

Appendix D

Table of results for One-Way ANOVA randomization checks across personalisation.

ANOVA

		Sum of Squares	df	Mean Square	F	Sig.
age	Between Groups	,232	1	,232	,007	,934
	Within Groups	5146,903	153	33,640		
	Total	5147,135	154			
smoker	Between Groups	,077	1	,077	,374	,542
	Within Groups	31,433	153	,205		
	Total	31,510	154			
gender	Between Groups	,485	1	,485	2,644	,106
	Within Groups	27,509	150	,183		
	Total	27,993	151			
english	Between Groups	,004	1	,004	,026	,873
	Within Groups	24,796	153	,162		
	Total	24,800	154			
prior_exp_total	Between Groups	1,255	1	1,255	,599	,440
	Within Groups	320,623	153	2,096		
	Total	321,877	154			

Appendix E.

Table of results for One-Way ANOVA randomization checks across empathy.

ANOVA

		Sum of Squares	df	Mean Square	F	Sig.
age	Between Groups	16,069	2	8,034	,238	,788
	Within Groups	5131,067	152	33,757		
	Total	5147,135	154			
smoker	Between Groups	,449	2	,225	1,099	,336
	Within Groups	31,060	152	,204		
	Total	31,510	154			
gender	Between Groups	,701	2	,351	1,914	,151
	Within Groups	27,292	149	,183		
	Total	27,993	151			
english	Between Groups	,055	2	,027	,169	,845
	Within Groups	24,745	152	,163		
	Total	24,800	154			
prior_exp_total	Between Groups	4,862	2	2,431	1,166	,315
	Within Groups	317,016	152	2,086		
	Total	321,877	154			